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The Efficiency Evaluation of Horizontal Ecological Compensation in the Wei River Basin of China Based on the Four-Stage DEA

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Abstract: This study aims to explore how the Wei River Basin can enhance the efficiency of horizontal ecological compensation to promote high-quality and sustainable development in the Yellow River Basin. To achieve this, a four-stage DEA (Data Envelopment Analysis) method was employed to evaluate the efficiency of ecological compensation in six prefecture-level cities within the Wei River Basin from 2001 to 2022. In addition, the K-prototype clustering analysis method was integrated to assess the regional differences in ECE (ecological compensation efficiency). The findings indicate: (1) the ecological compensation efficiency in the upstream areas of the Wei River Basin is significantly higher than in the downstream regions; (2) the influence of factors such as the proportion of the tertiary industry, population density and residents' disposable income on the efficiency of ecological compensation is significant; (3) after excluding environmental factors, the overall ecological compensation efficiency showed a significant improvement. Based on these insights, it is recommended that the provinces of Shaanxi and Gansu further establish a robust compensation fund operation mechanism, build a cross-regional ecological compensation upstream-downstream coordination system, and strengthen inter-basin economic cooperation mechanisms to promote dual-driven development through technological advancement and scale benefits, thereby advancing ecological protection and sustainable development in the Wei River Basin.

Key words: Wei River Basin, ecological compensation, efficiency evaluation, four-stage DEA.

1. Introduction

Ecological conservation and high-quality development in the Yellow River Basin represent a long-term project of vital importance for the great rejuvenation of the Chinese nation. Protecting the Yellow River is a major national strategy of China, which requires the coordinated advancement of cross-regional ecological collaborative governance within the basin. However, the horizontal ecological conservation compensation system in the Yellow River Basin still faces challenges, including a limited range of compensation entities, ill-defined compensation criteria, a compensation model primarily confined to monetary transfer (payment-based methods), and the lack of an effective dispute resolution mechanism [1].

The Wei River, the largest tributary of the Yellow River Basin, is a pioneer area for horizontal ecological compensation and also serves as a pilot area for the *Outline of the Plan for Ecological Protection and High-Quality Development in the Yellow River Basin*. In 2011, the signing of the *Framework Agreement for the Environmental Protection City Alliance in the Wei River Basin* between Shaanxi and Gansu provinces marked the beginning of autonomous horizontal ecological compensation within river basins in China. According to publicly available data from the Shaanxi Provincial Department of Finance, the Gansu Provincial Department of Ecology and Environment, and the YRCC (Yellow River Conservancy Commission), in 2023, the provincial finance of Shaanxi allocated 120 million yuan in

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ecological compensation funds for the Wei River Basin, while as of 2024, Gansu province had cumulatively arranged 80 million yuan in provincial incentive funds for the Wei River Basin. Although in 2023 the mainstream water quality of the Wei River consistently met the Class III standard, sections with Classes IV to V water quality still persisted. Furthermore, while the COD (Chemical Oxygen Demand) concentration decreased by 45% compared to 2015, agricultural non-point source pollution still contributed to over 50% of the total pollution load, indicating a mismatch between the effectiveness of ecological governance and the investment. Which specific factors lead to the low efficiency of horizontal ecological compensation in the Wei River Basin? Some scholars argue that issues within horizontal ecological compensation policies, such as imperfect legal regulations, unclear rights and obligations [2], narrow compensation scope [3] and unreasonable compensation standards [4] result in low utilization efficiency of compensation funds, making it difficult for ecological compensation funds to offset the opportunity costs incurred by upstream governments [5,6]. Improving ECE (ecological compensation efficiency) helps address problems such as non-transparent fund utilization and unscientific compensation standards within ecological compensation schemes, and can simultaneously enhance ecological, economic, and social benefits, thereby strengthening the implementation effectiveness of horizontal ecological compensation policies [7].

Studies on ecological compensation efficiency primarily employ quantitative analytical methods such as DEA (Data Envelopment Analysis) [8], SFA (Stochastic Frontier Analysis) [9], Malmquist index analysis [10,11] and DID (Difference-in-Differences) [12,13] for evaluation. The traditional DEA model proposed by Charnes [14] in 1978 evaluates the efficiency of decision-making units by attributing slack to managerial inefficiency; however, this approach neglects the impacts of external environmental factors and random errors on efficiency values, and cannot directly analyze dynamic efficiency changes. Conversely, SFA (Stochastic Frontier Analysis) requires predefining the functional form of the production function and the distribution of inefficiency terms. Such assumptions may lead to model misspecification bias, compromising the accuracy of efficiency evaluations [15]. DID necessitates parallel trends between treatment and control groups prior to policy implementation. Yet, systematic differences in natural resource endowments and economic foundations between pilot and non-pilot areas of ecological compensation policies may violate this assumption [16] Scholars often integrate DEA with methods such as SFA, Tobit models, Malmquist index analysis, and entropy weighting [17-20]. Although the three-stage DEA model proposed by Fried et al. [21] combines the strengths of DEA and SFA to partially address environmental interference, it still suffers from high sample dependence, computational complexity, and inadequate dynamic efficiency analysis. The Tobit model outperforms SFA in handling censored data, enabling more accurate separation of environmental factors, managerial inefficiency, and stochastic noise. Unlike SFA’s linear regression assumptions, the Tobit model better aligns with real-world contexts, offers enhanced interpretability and applicability, and is particularly suited for data with upper/lower bound constraints.

Therefore, using the Wei River as a case study, this paper adopts a refined four-stage DEA method integrating DEA with a Tobit model. Leveraging data from six prefecture-level cities in the Wei River Basin from 2001 to 2022, we systematically evaluate input-output efficiency. Concurrently, K-prototype clustering analysis is employed to provide data-driven insights for Shaanxi and Gansu Provinces in assessing recent horizontal ecological compensation policy effectiveness and dynamically adjusting such policies. This contributes to establishing and refining ecological protection compensation systems aligned with socio-economic development.

2. Model

The foundational DEA models comprise two variants: BCC [22] and CCR [14]. The CCR model assumes CRS (constant returns to scale), which often deviates from real-world conditions; therefore, Banker et al. (1984) developed the DEA-BCC model incorporating VRS (variable returns to scale). This model evaluates m DMUs (decision-making units), each with n inputs and s outputs, where all input and output values are non-negative. The DEAP 2.1 software was utilized to compute efficiency scores for each DMU, encompassing TE (technical efficiency), PTE (pure technical efficiency), SE (scale efficiency), and input slack variables. These efficiency metrics adhere to the relationship: TE = PTE × SE.

In the second stage, since the DEA efficiency scores derived from the DEA-BCC model fail to exclude interference from external environmental factors, a Tobit regression model was employed to mitigate the impact of environmental variables on efficiency evaluation. The efficiency scores and input slack variables obtained from the DEA-BCC model served as the explained variables, while environmental variables functioned as explanatory variables to construct the Tobit regression model.

In the third stage, the original input values of each DMU were adjusted based on the regression results from the Tobit model.

$$x_{ik}^{adj} = x_{ik} + \left[max^{k}\{\hat{s}_{ik}\} - \hat{s}_{ik}\right], \quad i = 1,2,\ldots,M; k = 1,2,\ldots,N \tag{1}$$

where x_{ik}^{adj} denotes the value of the k-th input indicator for the i-th DMU (decision-making unit) after eliminating the influence of environmental variables, k in x_{ik} represents the corresponding actual input indicator value, and max{ } refers to the maximum fitted slack variable within each column of data.

In the fourth stage of the model, the adjusted input indicator values and the unchanged output indicator values are incorporated into the DEA-BCC model. Following the adjustment in the third stage, all DMUs have eliminated the effects of external environmental factors and are thus operating under homogeneous environmental conditions. The efficiency values are then recalculated following the initial BCC model procedure, yielding adjusted efficiency values.

3. Indicators and Data Sources

3.1 Indicator Construction

3.1.1 Input-Output Variables

During the construction of the DEA model, to prevent distortion in efficiency evaluation, the total number of input and output indicators must not exceed half the number of DMUs (decision-making units). As specified in Table 1, this study selects six prefecture-level cities in the Wei River Basin as DMUs. Drawing on the analytical approach of Qu et al. [23] for environmental efficiency in national key ecological functional zones, public fiscal expenditure and year-end employed population are chosen as input indicators from the labor and capital dimensions to reflect financial and labor inputs for environmental management. Jin et al. [24] demonstrated the feasibility and necessity of incorporating GEP (Gross Ecosystem Product) into ecological compensation performance assessments; consequently; GEP is selected as the output indicator. Definitions: (1) Public fiscal expenditure denotes government expenditures on public affairs and services within a fiscal year. (2) Year-end employed population refers to the total number of employed individuals in a region at a specific time point (typically year-end). (3) GEP (Gross Ecosystem Product) represents the aggregated value of products and services provided by ecosystems for human well-being and sustainable socio-economic development.

3.1.2 Environmental Variables

Environmental factors, also termed external factors, refer to elements that cannot be controlled or altered in the short term but influence the efficiency of horizontal eco-compensation. Adopting the methodology of Zhao and Song [25] in environmental governance efficiency research, the proportion of the tertiary industry, population density, and resident disposable income

Table 1 Indicator Construction.

Indicator Type	Collective Indicators
input Indicators	Public fiscal expenditure
	Year-end employed population
Output Indicators	Gross Ecosystem Product (GEP)
Environmental Variables	Proportion of tertiary industry
	Student Population Density at Secondary Level
	Resident disposable income per capita

were selected as environmental variables for efficiency analysis. Higher levels of resident education foster greater social responsibility and enhance receptiveness to market-oriented, diversified ecological conservation compensation mechanisms [26]. Considering disparities in economic development levels and educational resource allocation across the Wei River Basin, while general population density data are readily available, it lacks the targeted explanatory power of "secondary student population density", which more precisely reflects the impact of regional educational resource distribution and future labor quality on eco-compensation efficiency. Consequently, the proportion of the tertiary industry, secondary student population density, and resident disposable income are selected as environmental variables. Definitions: (1) Proportion of the tertiary industry denotes the ratio of value-added by the tertiary sector to the regional GDP (Gross Domestic Product). Regions with a high proportion of the tertiary industry typically exhibit higher value-added and lower energy consumption. (2) Secondary student population density refers to the ratio of the number of secondary students to the land area within a defined region. (3) Resident disposable income represents the total annual household income available for final consumption and savings.

3.2 Data Sources

The Wei River Basin is an important component of the Yellow River Basin. It originates from Niaoshu Mountain in Dingxi City, Gansu Province, flows through Dingxi and Tianshui in Gansu, and Baoji, Xianyang, Xi'an, and Weinan in Shaanxi, finally joining the Yellow River at Tongguan. Dingxi and Tianshui are located in the upper reaches, Baoji and Xianyang in the middle reaches, and Xi'an and Weinan in the lower reaches. Meanwhile, since the 1990s, China's statistical yearbook system has been progressively refined, with the environmental and urban-rural development data and indicators in the *Gansu Statistical Yearbooks* and *Shaanxi Statistical Yearbooks* becoming more comprehensive and systematic. Therefore, this study utilizes data on input-output variables and environmental variables from 2001 to 2022 for the six prefecture-level cities in the upper, middle, and lower reaches of the Wei River Basin, sourced primarily from the *Gansu Statistical Yearbook*, *Shaanxi Statistical Yearbook*, and *China Urban-Rural Construction Statistical Yearbook*.

4. Empirical Analysis

4.1 Empirical Results of DEA Model

Using DEAP 2.1 software, input-output indicators data from six prefecture-level cities during 2001-2022 were calculated to derive TE (technical efficiency), PTE (pure technical efficiency), and SE (scale efficiency).

4.1.1 Pure Technical Efficiency

Within the Wei River Basin, PTE values exhibit significant regional disparities, with mid-upper reaches demonstrating markedly higher efficiency than downstream areas. As observed in Table 2 Dingxi, Tianshui, and Baoji regions maintain relatively high PTE levels, achieving unity in specific years. This indicates efficient utilization of fiscally-provided ecological compensation funds in these regions, with minimal wastage and sound fund management practices. Xianyang, Xi'an, and Weinan exhibit lower PTE values, likely attributable to ineffective administration and suboptimal implementation of fiscal ecological compensation funds.

4.1.2 Scale Efficiency

Within the Wei River Basin, SE (scale efficiency) demonstrates minimal variation across upper, middle,

Table 2 Stage I pure technical efficiency (PTE) results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	1	0.87	1	0.586	0.236	0.279	0.66
2002	0.999	0.775	0.964	0.534	0.199	0.634	0.68
2003	1	0.769	1	0.492	0.171	0.582	0.67
2004	1	0.749	1	0.442	0.15	0.518	0.64
2005	0.98	0.62	0.999	0.378	0.13	0.376	0.58
2006	0.971	0.577	1	0.294	0.104	0.347	0.55
2007	0.979	0.622	0.979	0.27	0.078	0.367	0.55
2008	0.967	0.659	0.934	0.255	0.054	0.334	0.53
2009	1	0.68	1	0.266	0.045	0.341	0.56
2010	0.952	0.649	1	0.259	0.035	0.316	0.54
2011	0.898	0.612	0.805	0.121	0.031	0.258	0.45
2012	0.878	0.614	0.896	0.103	0.029	0.259	0.46
2013	0.634	0.58	0.672	0.172	0.026	0.369	0.41
2014	0.657	0.6	0.664	0.171	0.026	0.21	0.39
2015	0.693	0.612	0.662	0.17	0.026	0.035	0.37
2016	0.669	0.524	0.649	0.167	0.025	0.215	0.37
2017	0.687	0.506	0.627	0.195	0.022	0.206	0.37
2018	0.786	0.54	0.646	0.203	0.022	0.229	0.40
2019	0.736	0.516	0.656	0.218	0.021	0.235	0.40
2020	0.712	0.495	0.745	0.206	0.186	0.24	0.43
2021	0.686	0.509	0.771	0.205	0.021	0.241	0.41
2022	0.67	0.506	0.744	0.206	0.019	0.24	0.40

and lower reaches. As shown in Table 3, prior to 2010, Dingxi, Tianshui, and Baoji in the upper-middle reaches occasionally achieved SE values approaching unity, significantly exceeding those in middle-lower reaches. This indicates relatively balanced scales between ecological conservation and economic development in these regions before implementing the ecological compensation mechanism. Xianyang exhibited the lowest SE, suggesting issues of resource misallocation or diseconomies of scale. Notably, post-2010 witnessed substantial SE growth in Xianyang, Xi'an, and Weinan of the lower reaches. This phenomenon may correlate with Shaanxi Province's intensified ecological protection measures and implementation of the Wei River Basin ecological compensation mechanism. Concurrently, Dingxi, Tianshui, and Baoji experienced initial SE declines followed by recovery. Overall, ecological preservation and economic development scales remain in equilibrium across most areas of the Wei River Basin.

4.1.3 Ecological Compensation Efficiency

Table 4 presents the ecological compensation efficiency measurements for the Wei River Basin from 2001 to 2022. Fluctuations in efficiency across cities align closely with the basin-wide trend. Dingxi's efficiency peaked in 2001 and 2003 before declining progressively, plunging to 0.632 by 2013. Tianshui maintained stability during 2001 and 2009 but deteriorated markedly post-2010, falling to approximately 0.5. Baoji demonstrated high early-phase efficiency approaching 1.0. Despite post-2010 declines, it retained relatively superior performance with minor recovery in 2019. Xianyang exhibited persistently low efficiency throughout the study period, consistently below 0.2 after 2011. Xi'an's efficiency remained below 0.03 post-2010, indicating critically deficient performance. Weinan experienced significant volatility during 2001-2009, declined post-2010, yet showed marginal recovery after 2018. Collectively, Tianshui and Baoji delivered optimal efficiency outcomes, whereas Xi'an demonstrated the

Table 3 Stage I scale efficiency (SE) results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	1	0.954	1	0.464	0.724	0.955	0.85
2002	0.799	0.994	0.997	0.497	0.709	0.603	0.77
2003	1	0.994	1	0.557	0.662	0.691	0.82
2004	0.946	0.994	0.999	0.618	0.693	0.781	0.84
2005	0.827	0.997	0.988	0.674	0.705	0.932	0.85
2006	0.782	0.997	0.976	0.902	0.665	0.997	0.89
2007	0.983	0.994	0.931	0.883	0.682	0.98	0.91
2008	0.972	0.991	0.963	0.916	0.708	0.997	0.92
2009	1	0.997	1	0.959	0.849	0.99	0.97
2010	0.979	0.999	0.943	0.947	0.995	0.99	0.98
2011	0.937	0.993	0.98	0.859	0.994	0.985	0.96
2012	0.973	0.984	0.955	0.917	0.991	0.992	0.97
2013	0.997	0.984	0.97	0.847	0.991	0.986	0.96
2014	0.997	0.996	0.965	0.835	0.98	0.949	0.95
2015	0.997	0.98	0.956	0.844	0.972	0.813	0.93
2016	0.999	0.988	0.956	0.811	0.975	0.917	0.94
2017	0.979	0.99	0.958	0.777	0.98	0.898	0.93
2018	1	0.989	0.957	0.801	0.979	0.922	0.94
2019	0.998	0.987	0.957	0.794	0.982	0.932	0.94
2020	0.995	0.99	0.955	0.833	0.987	0.974	0.96
2021	0.997	0.988	0.955	0.862	0.986	0.973	0.96
2022	0.998	0.988	0.956	0.837	1	0.965	0.96

Table 4 Stage I ecological compensation efficiency results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	1	0.83	1	0.272	0.171	0.267	0.61
2002	0.799	0.771	0.961	0.266	0.141	0.382	0.59
2003	1	0.764	1	0.274	0.113	0.402	0.63
2004	0.946	0.745	0.999	0.273	0.104	0.405	0.62
2005	0.811	0.618	0.987	0.255	0.091	0.35	0.58
2006	0.759	0.575	0.976	0.265	0.069	0.346	0.57
2007	0.962	0.618	0.911	0.238	0.053	0.36	0.59
2008	0.94	0.653	0.899	0.233	0.038	0.333	0.57
2009	1	0.678	1	0.255	0.038	0.337	0.60
2010	0.932	0.649	0.943	0.245	0.034	0.313	0.58
2011	0.842	0.608	0.788	0.104	0.031	0.254	0.50
2012	0.855	0.604	0.856	0.095	0.029	0.257	0.51
2013	0.632	0.571	0.652	0.145	0.026	0.364	0.47
2014	0.655	0.597	0.641	0.143	0.025	0.199	0.44
2015	0.691	0.6	0.633	0.144	0.026	0.028	0.42
2016	0.668	0.518	0.62	0.136	0.025	0.197	0.44
2017	0.672	0.501	0.6	0.151	0.021	0.185	0.44
2018	0.785	0.534	0.618	0.162	0.021	0.211	0.46
2019	0.734	0.51	0.628	0.173	0.02	0.218	0.46
2020	0.708	0.49	0.712	0.171	0.184	0.234	0.50
2021	0.684	0.503	0.736	0.177	0.02	0.235	0.47
2022	0.669	0.5	0.711	0.173	0.019	0.231	0.47

lowest performance. The Shaanxi-based triad (Xianyang, Xi'an, Weinan) exhibited substantially inferior efficiency due to suboptimal PTE (pure technical efficiency).

The basin-wide efficiency manifests distinct phased variations. During the initial period (2001-2009), mean efficiency ranged between 0.57-0.63, reflecting relatively high efficacy. However, commencing in 2010, efficiency progressively declined, reaching its nadir in 2015 (mean: 0.42). A transient rebound emerged in 2020, yet overall efficiency failed to restore pre-2010 levels, fluctuating between 0.44-0.50. Given minimal SE fluctuations, the post-2010 efficiency deterioration primarily stemmed from fund mismanagement or technological obsolescence. Particularly in upper reaches, this signifies suboptimal eco-benefit output relative to resource inputs since the 2011 horizontal ecological compensation implementation, indicating limited policy effectiveness. Conversely, the 2020 efficiency improvement principally originated from enhanced PTE and SE in middle-lower reaches. This likely correlates with the 2020 Pilot Implementation *Plan for Supporting the Establishment of Horizontal Ecological Compensation Mechanisms across the Entire Yellow River Basin* (Cai Zi Huan [2020] No. 20) issued by the Ministry of Finance, Ministry of Ecology and Environment, Ministry of Water Resources, and National Forestry and Grassland Administration.

4.2 Analysis of Tobit Model Regression Results

External environmental factors exert significant influences on efficiency evaluation, potentially leading to biased estimations of efficiency relative to the actual environmental realities, thereby failing to accurately and objectively reflect the true circumstances. To rectify this issue, this paper selects the input slack variables of the six prefecture-level cities as the dependent variables and the environmental variables as the independent variables, constructing a Tobit regression model aimed at enhancing the precision of environmental efficiency assessment. The regression results are presented in Table 5. When the regression coefficient is negative, an increase in the environmental variables facilitates a reduction in input slack. In this scenario, the same output can be achieved with less input, leading to an improvement in ecological compensation efficiency. Conversely, when the regression coefficient is positive, an increase in external environmental variables will increase input slack or augment undesirable outputs. Here, additional inputs are required to achieve the same output, or the same inputs yield reduced output, consequently diminishing ecological compensation efficiency.

Tobit regression analysis was conducted with Public fiscal expenditure as the dependent variable. The regression coefficient for the Proportion of tertiary industry was -0.006 and showed significance at the 0.01 level ($z = -2.579$, $p = 0.010 < 0.01$), indicating that the Proportion of tertiary industry had a significant negative effect on Public fiscal expenditure; specifically, an increase in the proportion of the tertiary industry. The regression coefficient for Disposable income per capita was 0.000 and showed significance at the 0.01 level ($z = 6.297$, $p < 0.001 < 0.01$), indicating that Disposable income per capita had a significant positive effect on Public fiscal expenditure. The regression coefficient for Student Population Density at Secondary Level was 0.057 and showed significance at the 0.01 level ($z = 2.688$, $p = 0.007 < 0.01$), indicating that Student Population Density at Secondary Level had a significant positive effect on Public fiscal expenditure. The significant negative correlation between the Proportion of tertiary industry and Public fiscal expenditure arises because the tertiary industry typically exhibits lower pollution characteristics and has a smaller negative environmental impact compared to the primary and secondary industries. Therefore, an increase in the proportion of the tertiary industry may signal environmental improvement, thus potentially prompting the government to reduce funding for environmental protection, decrease fiscal expenditure redundancy, and enhance ecological compensation efficiency. The significant positive correlations of Disposable income per capita and SPDSL (Student Population Density at Secondary Level) with Public fiscal expenditure imply that increases in Disposable income per capita and population density may lead to greater investment in environmental protection due to increased fiscal revenues, potentially resulting in fiscal expenditure redundancy and a reduction in ecological compensation efficiency.

The regression results for Year-End Employment reveal that: the regression coefficient for the Proportion of tertiary industry was 0.000 but did not show significance (z = 1.560, p = 0.119 > 0.05), indicating that the Proportion of tertiary industry has no significant effect on Year-End Employment. The regression coefficient for Disposable income per capita was -0.000 and showed significance at the 0.01 level (z = -6.371, p < 0.001 < 0.01), indicating that Disposable income per capita has a significant negative effect on Year-End Employment. The regression coefficient for Student Population Density at Secondary Level was -0.014 and showed significance at the 0.01 level (z = -5.150, p < 0.001 < 0.01), indicating that Student Population Density at Secondary Level has a significant negative effect on Year-End Employment. The significant negative correlations of Disposable income per capita and Student Population Density at Secondary Level with Year-End Employment imply that increases in Disposable income per capita and population density may, by promoting technological innovation and industrial upgrading, reduce Labor reliance, thereby decreasing redundancy in Year-End Employment and enhancing ecological compensation efficiency. Furthermore, an increase in Disposable income per capita is typically accompanied by rising labor costs, prompting enterprises to seek more efficient production methods, reduce Labor reliance, consequently decreasing redundancy in Year-End Employment and enhancing Ecological Compensation Efficiency.

Overall, increasing the Proportion of tertiary industry reduces fiscal expenditure redundancy in Public fiscal expenditure, which is conducive to improving ecological compensation efficiency; increasing Disposable income per capita and population density may lead to a reduction in labor input for ecological compensation and an increase in investment in environmental protection.

4.3 Stage III

Based on the fitted lines from the Tobit regression model, the parameters required for the following formulas were calculated:

Fiscal expenditure redundancy = -0.086 - 0.006 * Proportion of tertiary industry + 0.000 * Disposable income per capita + 0.057 * Student Population Density at Secondary Level.

Redundancy in Year-End Employment = 0.030 + 0.000 * Proportion of tertiary industry - 0.000 * Disposable income per capita - 0.014 * Student Population Density at Secondary Level.

Table 5 Tobit regression results for ecological compensation efficiency evaluation.

Explanatory variables	Dependent variables	
	Public fiscal expenditure	Year-end employment
Intercept	-0.086* (-2.294)	0.030** (6.256)
Proportion of tertiary industry	-0.006** (-2.579)	0.000 (1.560)
Disposable income per capita	0.000** (6.297)	-0.000** (-6.371)
Student population density at secondary level	0.057** (2.688)	-0.014** (-5.150)
Log (Sigma)	-2.268** (-36.714)	-4.336** (-70.179)
Observations	132	132
Likelihood Ratio Test	χ^2 (3) = 37.044, p = 0.000	χ^2 (3) = 44.787, p = 0.000
McFadden R^2	-0.200	-0.062

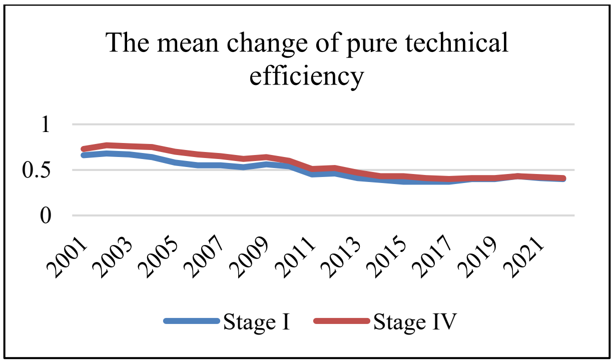

Fig. 1 Changes in pure technical efficiency.

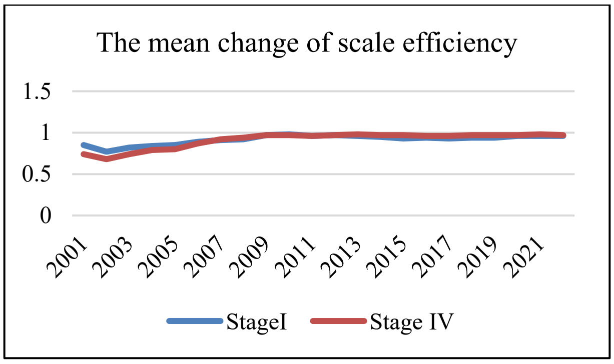

Fig. 2 Changes in scale efficiency.

By adjusting the initial input parameters and eliminating the interference of exogenous environmental factors on the current environmental efficiency assessment, this stage enhances the accuracy of the efficiency evaluation, reducing randomness and bias caused by specific regional factors.

4.4 Stage IV Regression Results

As shown by the data in Fig. 1 and Fig. 2, after incorporating the environmental variables, the recalculated values of Pure technical efficiency and Scale efficiency changed in most cases. This fully demonstrates that the influence of environmental variables on efficiency values cannot be ignored. Therefore, the interference of environmental variables should be eliminated when evaluating efficiency values.

4.4.1 Pure Technical Efficiency and Scale Efficiency

Based on the data in Table 6 and Table 2, the following findings are evident after eliminating environmental factors: (1) The overall Pure technical efficiency of ecological compensation showed significant improvement. This indicates that Disposable income per capita and Student Population Density at Secondary Level constrain the compensation efficiency. Among them, the change in Pure technical efficiency for Baoji City was relatively limited, indicating the stability of its external environmental factors, which did not exert a significant impact on Pure technical efficiency. (2) Compared with Stage 1, Dingxi City and Tianshui City exhibited a decline in Pure technical efficiency. This may be attributed to their favorable external environmental conditions; post-adjustment, the efficiency values consequently showed a decrease. (3) In other prefecture-level cities, the mean Pure technical efficiency increased, with Xi'an City showing the most prominent growth. If the influence of environmental factors were neglected, the Pure technical efficiency of these cities might have been underestimated. Overall, similar to Stage 1, the distribution of Pure technical efficiency still shows higher values in the Dingxi, Tianshui, and Baoji areas compared to the Xianyang, Xi'an, and Weinan areas, and higher values in the mid-upper reaches compared to the downstream areas.

Based on the data in Table 7 and Table 3, after eliminating the effects of environmental factors, it can be observed that: (1) The SE (scale efficiency) of Dingxi City from 2001 to 2022 decreased compared to the first stage. (2) The SE (scale efficiency) of Tianshui, Xianyang, and Weinan decreased before 2011 but increased after 2011. (3) The SE (scale efficiency) of Baoji and Xi'an regions increased compared to the first stage. Overall, consistent with the first stage, SE (scale efficiency) still exhibited a distribution where the Dingxi, Tianshui, and Baoji regions were higher than the Xianyang, Xi'an, and Weinan regions.

4.4.2 Ecological Compensation Efficiency

Based on data from Table 8 and Table 4, after eliminating the effects of environmental factors, it is found that the ecological compensation efficiency values of all regions except Dingxi and Tianshui were higher than those in the first stage, with Xi'an exhibiting

Table 6 Stage IV pure technical efficiency (PTE) results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	1.00	0.889 (+)	1.00	0.689 (+)	0.440 (+)	0.39 (+)	0.73 (+)
2002	0.997 (-)	0.790 (+)	0.983 (+)	0.671 (+)	0.418 (+)	0.761 (+)	0.77 (+)
2003	1.00	0.775 (+)	1.00	0.651 (+)	0.38 (+)	0.751 (+)	0.76 (+)
2004	1.00	0.748 (-)	1.00	0.61 (+)	0.389 (+)	0.725 (+)	0.75 (+)
2005	1 (+)	0.662 (+)	0.989 (-)	0.563 (+)	0.393 (+)	0.602 (+)	0.70 (+)
2006	1 (+)	0.605 (+)	1.00	0.475 (+)	0.361 (+)	0.570 (+)	0.67 (+)
2007	0.989 (+)	0.598 (-)	0.98 (+)	0.414 (+)	0.361 (+)	0.568 (+)	0.65 (+)
2008	0.951 (-)	0.592 (-)	0.943 (+)	0.38 (+)	0.327 (+)	0.512 (+)	0.62 (+)
2009	1.00	0.583 (-)	1.00	0.397 (+)	0.350 (+)	0.488 (+)	0.64 (+)
2010	0.905 (-)	0.563 (-)	1.00	0.376 (+)	0.340 (+)	0.445 (+)	0.60 (+)
2011	0.75 (-)	0.538 (-)	0.825 (+)	0.268 (+)	0.332 (+)	0.368 (+)	0.51 (+)
2012	0.634 (-)	0.541 (-)	0.956 (+)	0.267 (+)	0.334 (+)	0.359 (+)	0.52 (+)
2013	0.443 (-)	0.496 (-)	0.747 (+)	0.279 (+)	0.329 (+)	0.554 (+)	0.47 (+)
2014	0.447 (-)	0.512 (-)	0.74 (+)	0.271 (+)	0.327 (+)	0.312 (+)	0.43 (+)
2015	0.441 (-)	0.517 (-)	0.741 (+)	0.269 (+)	0.337 (+)	0.264 (-)	0.43 (+)
2016	0.414 (-)	0.449 (-)	0.725 (+)	0.262 (+)	0.329 (+)	0.305 (+)	0.41 (+)
2017	0.398 (-)	0.433 (-)	0.693 (+)	0.258 (+)	0.313 (+)	0.296 (+)	0.40 (+)
2018	0.425 (-)	0.448 (-)	0.708 (+)	0.263 (+)	0.328 (+)	0.313 (+)	0.41 (+)
2019	0.406 (-)	0.446 (-)	0.700 (+)	0.265 (+)	0.329 (+)	0.318 (+)	0.41 (+)
2020	0.402 (-)	0.425 (-)	0.747 (+)	0.27 (+)	0.406 (+)	0.33 (+)	0.43 (+)
2021	0.387 (-)	0.434 (-)	0.764 (-)	0.275 (+)	0.349 (+)	0.314 (+)	0.42 (+)
2022	0.386 (-)	0.431 (-)	0.741 (-)	0.272 (+)	0.320 (+)	0.312 (+)	0.41 (+)

Table 7 Stage IV scale efficiency (SE) results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	0.52 (-)	0.625 (-)	1	0.457 (-)	0.9 (+)	0.946 (-)	0.74 (-)
2002	0.452 (-)	0.675 (-)	0.98 (-)	0.47 (-)	0.916 (+)	0.569 (-)	0.68 (-)
2003	0.665 (-)	0.724 (-)	1	0.517 (-)	0.912 (+)	0.642 (-)	0.74 (-)
2004	0.764 (-)	0.777 (-)	1 (+)	0.56 (-)	0.941 (+)	0.712 (-)	0.79 (-)
2005	0.767 (-)	0.776 (-)	0.999 (+)	0.581 (-)	0.945 (+)	0.744 (-)	0.80 (+)
2006	0.85 (+)	0.832 (-)	1 (+)	0.748 (-)	0.937 (+)	0.846 (-)	0.87 (+)
2007	0.904 (-)	0.912 (-)	0.999 (+)	0.836 (-)	0.958 (+)	0.926 (-)	0.92 (+)
2008	0.931 (-)	0.929 (-)	0.997 (+)	0.875 (-)	0.989 (+)	0.921 (-)	0.94 (+)
2009	0.989 (-)	0.957 (-)	1	0.905 (-)	0.992 (+)	0.952 (-)	0.97 (+)
2010	0.977 (-)	0.967 (-)	0.964 (+)	0.933 (-)	0.992 (-)	0.979 (-)	0.97 (+)
2011	0.951 (+)	0.984 (-)	0.999 (+)	0.874 (+)	0.992 (-)	0.967 (-)	0.96 (+)
2012	0.973	0.992 (+)	0.999 (+)	0.899 (-)	0.992 (+)	0.978 (-)	0.97 (+)
2013	0.988 (+)	0.993 (+)	0.999 (+)	0.887 (+)	0.992 (+)	0.996 (+)	0.98 (+)
2014	0.99 (-)	0.993 (-)	0.999 (+)	0.882 (+)	0.991 (+)	0.952 (+)	0.97 (+)
2015	0.99 (-)	0.993 (+)	0.999 (+)	0.888 (+)	0.992 (+)	0.955 (+)	0.97 (+)
2016	0.989 (-)	0.992 (+)	0.999 (+)	0.877 (+)	0.992 (+)	0.939 (+)	0.96 (+)
2017	0.976 (-)	0.991 (+)	0.999 (+)	0.866 (+)	0.991 (+)	0.926 (+)	0.96 (+)
2018	0.989 (-)	0.992 (+)	0.999 (+)	0.877 (+)	0.992 (+)	0.942 (+)	0.97 (+)
2019	0.99 (-)	0.992 (+)	0.999 (+)	0.875 (+)	0.992 (+)	0.948 (+)	0.97 (+)
2020	0.99 (-)	0.991 (+)	0.999 (+)	0.891 (+)	0.992 (+)	0.974	0.97 (+)
2021	0.99 (-)	0.992 (+)	0.999 (+)	0.904 (+)	0.992 (+)	0.973	0.98 (+)
2022	0.989 (-)	0.992 (+)	0.999 (+)	0.893 (+)	0.991 (-)	0.968 (+)	0.97 (+)

Table 8 Stage IV ecological compensation efficiency (ECE) results of ecological.

Year	Dingxi	Tianshui	Baoji	Xianyang	Xi'an	Weinan	Mean
2001	0.52 (-)	0.555 (-)	1	0.315 (+)	0.396 (+)	0.369 (+)	0.53 (-)
2002	0.451 (-)	0.533 (-)	0.963 (+)	0.316 (+)	0.383 (+)	0.433 (+)	0.51 (-)
2003	0.665 (-)	0.561 (-)	1	0.337 (+)	0.347 (+)	0.482 (+)	0.57 (-)
2004	0.764 (-)	0.581 (-)	1 (+)	0.341 (+)	0.366 (+)	0.516 (+)	0.59 (+)
2005	0.767 (-)	0.514 (-)	0.988 (+)	0.327 (+)	0.372 (+)	0.448 (+)	0.57 (+)
2006	0.85 (+)	0.503 (-)	1 (+)	0.355 (+)	0.338 (+)	0.482 (+)	0.59 (+)
2007	0.894 (-)	0.545 (-)	0.979 (+)	0.346 (+)	0.346 (+)	0.525 (+)	0.61 (+)
2008	0.885 (-)	0.55 (-)	0.94 (+)	0.332 (+)	0.324 (+)	0.472 (+)	0.58 (+)
2009	0.989 (+)	0.558 (-)	1	0.359 (+)	0.347 (+)	0.465 (+)	0.62 (+)
2010	0.884 (-)	0.544 (-)	0.964 (+)	0.351 (+)	0.337 (+)	0.436 (+)	0.59 (+)
2011	0.714 (-)	0.529 (-)	0.824 (+)	0.234 (+)	0.329 (+)	0.356 (+)	0.50 (+)
2012	0.617 (-)	0.537 (-)	0.955 (+)	0.24 (+)	0.331 (+)	0.352 (+)	0.51 (+)
2013	0.437 (-)	0.493 (-)	0.746 (+)	0.247 (+)	0.326 (+)	0.552 (+)	0.47 (+)
2014	0.442 (-)	0.509 (-)	0.739 (+)	0.239 (+)	0.324 (+)	0.297 (+)	0.43 (+)
2015	0.436 (-)	0.513 (-)	0.74 (+)	0.239 (+)	0.334 (+)	0.252 (+)	0.42 (+)
2016	0.41 (-)	0.445 (-)	0.725 (+)	0.23 (+)	0.326 (+)	0.286 (+)	0.40 (+)
2017	0.389 (-)	0.429 (-)	0.692 (+)	0.224 (+)	0.31 (+)	0.275 (+)	0.39 (+)
2018	0.42 (-)	0.444 (-)	0.707 (+)	0.231 (+)	0.325 (+)	0.295 (+)	0.40 (+)
2019	0.402 (-)	0.442 (-)	0.699 (+)	0.232 (+)	0.326 (+)	0.301 (+)	0.40 (+)
2020	0.398 (-)	0.421 (-)	0.746 (+)	0.24 (+)	0.403 (+)	0.322 (+)	0.42 (+)
2021	0.383 (-)	0.43 (-)	0.763 (+)	0.249 (+)	0.346 (+)	0.305 (+)	0.41 (+)
2022	0.381 (-)	0.428 (-)	0.741 (+)	0.243 (+)	0.317 (+)	0.302 (+)	0.40 (+)

the most substantial increase in ecological compensation efficiency. This indicates that mid-lower reach regions, particularly Xi'an, likely had higher taxes due to high population density and Disposable income per capita, leading to greater investment in environmental protection, resulting in fiscal expenditure redundancy that lowered their ecological compensation efficiency; consequently, after eliminating these environmental factors, their ecological compensation efficiency improved. The ecological compensation efficiency of Dingxi and Tianshui decreased by 26% and 17%, respectively, compared to the first stage, suggesting that their initially higher ecological compensation efficiency was closely associated with external environmental factors: Their relatively low Disposable income per capita and population density, underdeveloped economy, and low labor costs resulted in smaller investments in environmental protection, which boosted their ecological compensation efficiency; therefore, after eliminating these environmental factors, their ecological compensation efficiency declined.

4.5 Cluster Analysis

K-prototype clustering analysis was employed to classify the three types of efficiency values obtained from the efficiency evaluation of six prefecture-level cities over the period 2001-2022, resulting in the identification of three distinct clusters. These clusters accounted for 62.88%, 23.48%, and 13.64% of the observations, respectively, as detailed in Table 9. Significant differences were observed among the three clusters in terms of ecological compensation efficiency, pure technical efficiency, and scale efficiency. The cluster characterized by low ecological compensation efficiency, low pure technical efficiency, and medium scale efficiency constituted the largest proportion at 62.88%. This indicates that from 2001 to 2022, the primary reason for low efficiency in most of these six prefecture-level cities was low pure technical efficiency, stemming from poor management of horizontal ecological compensation funds and technological obsolescence, which hindered the maximization of

Table 9 ANOVA results for differences among clusters.

	ANOVA results for differences among clusters (Mean ± Standard Deviation)			F	p
	Cluster_1 (n = 83)	Cluster_2 (n = 31)	Cluster_3 (n = 18)		
Ecological compensation efficiency (θ)	0.37 ± 0.09	0.85 ± 0.12	0.46 ± 0.11	246.635	0.000^{**}
Pure technical efficiency	0.39 ± 0.09	0.88 ± 0.13	0.74 ± 0.15	242.486	0.000^{**}
Scale efficiency (k)	0.95 ± 0.05	0.97 ± 0.06	0.62 ± 0.11	220.405	0.000^{**}

Table 10 Cluster analysis of ecological compensation efficiency (2022).

	Cluster_1 (n = 5)	Cluster_2 (n = 1)
Technical efficiency	0.44 ± 0.18	0.27 ± null
Scale efficiency (k)	0.99 ± 0.01	0.89 ± null
Overall efficiency (θ)	0.43 ± 0.18	0.24 ± null

eco-benefit outputs and resulted in a predominantly low-efficiency state for ecological compensation. The cluster exhibiting high ecological compensation efficiency, high pure technical efficiency, and high scale efficiency accounted for a moderate proportion of 23.48%. Among the six prefecture-level cities experiencing low ecological compensation efficiency, only 13.64% were attributed to inefficient scale of capital input and poor management of ecological compensation funds.

Focusing specifically on the ecological compensation efficiency within the Wei River Basin for the year 2022, K-prototype clustering analysis was applied, yielding two distinct clusters as presented in Table 10. According to the classification results, only Xianyang fell into the high-tier cluster in 2022, while all other prefecture-level cities were classified into the low-tier cluster.

5. Research Conclusions and Policy Recommendations

The evaluation of ecological compensation efficiency levels in the Wei River Basin reveals that ecological compensation policies implemented at various stages have yielded some positive outcomes. However, persistent issues such as poor management of horizontal ecological compensation funds, technological obsolescence, and inefficient scale of capital input continue to result in suboptimal efficiency. Therefore, establishing a robust compensation fund operation mechanism, developing a cross-regional ecological compensation upstream-downstream coordination system, and fostering inter-basin economic cooperation mechanisms are imperative. These measures aim to achieve dual enhancement of "technology and scale", which is not only essential for refining horizontal ecological compensation policy but also constitutes a critical step for advancing ecological protection and sustainable development within the region.

5.1 Research Conclusions

The ecological compensation efficiency of Dingxi, Tianshui, and Baoji within the Wei River Basin is significantly higher than that of Xianyang, Xi'an, and Weinan. During the period 2001 and 2022, Dingxi, Tianshui, and Baoji exhibited relatively high ecological compensation efficiency, while Xianyang, Xi'an, and Weinan showed lower ecological compensation efficiency values. This indicates that Dingxi, Tianshui, and Baoji utilize fiscally-provided ecological compensation funds relatively efficiently, with minimal waste and sound fund management practices. Deficiencies remain in the investment and management of ecological compensation funds in Xianyang, Xi'an, and Weinan. Prior to 2010, the scale efficiency in the upper reaches of the Wei River Basin was close to 1, significantly higher than that in the middle and lower reaches. This suggests that before the implementation of the ecological compensation mechanism, the scale of ecological environment and economic development in the upper reaches was relatively reasonable. Since 2010, a significant decline in ecological compensation efficiency occurred in the upstream areas of Dingxi and Tianshui due to decreases in both pure technical efficiency and scale efficiency. Therefore, the current priority for the Wei River Basin's horizontal ecological compensation policy should be optimizing fund structure, fund management, and rational resource allocation to enhance ecological compensation efficiency.

After eliminating the influence of environmental variables in the third stage, the overall ecological compensation efficiency level showed a significant improvement. Compared to the first stage, the removal of environmental variables led to improvements in pure technical efficiency, scale efficiency, and ecological compensation efficiency in the upper reaches only during some years within the 2001-2022 period. Improvements were observed in pure technical efficiency, scale efficiency, and ecological compensation efficiency across the middle and lower reaches. Temporally, the mean ecological compensation efficiency value for the six prefecture-level cities fluctuated between 0.51 and 0.62 from 2001 to 2009, indicating relatively high efficiency. However, starting in 2010, ecological compensation efficiency gradually declined, reaching its lowest point of 0.39 in 2017. Although a rebound trend emerged from 2018 onwards, the overall level has not yet recovered to the high efficiency state of the 2001-2009 period. Regionally, a substantial gap exists in ecological compensation efficiency between the mid-upper reaches and the downstream areas of the Wei River Basin. The mean ecological compensation efficiency was 1.10 for upstream Dingxi and Tianshui, 1.14 for midstream Baoji and Xianyang, and 0.73 for downstream Xi'an and Weinan. This demonstrates that the three environmental variables—Proportion of tertiary industry, Disposable income per capita, and Student Population Density at Secondary Level—exert a significant influence on ecological compensation efficiency in the Wei River Basin, particularly in Dingxi, Tianshui, and Xi'an. Increasing the Proportion of tertiary industry helps reduce fiscal expenditure redundancy in Public fiscal expenditure and promotes ecological compensation efficiency. Consequently, the six regions in the Wei River Basin should optimize their industrial structure, develop knowledge-intensive industries, enhance environmental protection technology levels, and thereby improve ecological compensation efficiency. Increases in Disposable income per capita and Student Population Density at Secondary Level can reduce Labor reliance by driving technological advancement and increasing labor costs, ultimately enhancing ecological compensation efficiency. Therefore, the six regions should optimize labor input in environmental protection to improve ecological compensation efficiency.

5.2 Policy Recommendations

Establishing a compensation fund operation mechanism plays a crucial role in ensuring fund utilization efficiency, guaranteeing fund stability, and strengthening fund supervision. It is recommended to establish a comprehensive fund management system and regulations covering the entire process from fund raising, allocation, utilization, and supervision to budgeting, approval, disbursement, and accounting. Building on this, diversified fund-raising channels should be established, including government fiscal allocations, social capital participation, ecological compensation funds, and ecological water fee collection. The specific purposes of compensation funds should be clearly defined, such as ecosystem restoration, environmental pollution control, and livelihood compensation for residents in ecological protection areas, ensuring earmarked use and transparent utilization. During the ecological compensation process, fund allocation should be comprehensively determined based on the weights of various factors to ensure scientific and rational distribution. Industrial development funds should be set up, utilizing compensation funds through methods like equity investment and loan interest subsidies to enhance fund utilization efficiency.

It is essential to establish a cross-regional ecological compensation coordination system between upstream and downstream areas, along with inter-basin economic cooperation mechanisms. This provides robust support for comprehensively and multi-dimensionally promoting basin-wide ecological protection and sustainable development centered on the river basin. Effective negotiation between upstream and downstream areas can balance and resolve interest conflicts arising from shared basin resources, achieving common ecological protection goals; enhance infrastructure connectivity, including transportation facilities construction, energy facility interconnection, and information network sharing, to promote resource sharing across regions; cooperatively build industrial parks within the basin to achieve industrial cluster development, strengthen cooperation along the industrial chain, create complete industrial chains, increase industrial added value, and enhance regional industrial competitiveness; facilitate the flow and sharing of labor, capital, talent, technology, and academic resources across regions, and strengthen financial cooperation.

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