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Plant–Network Coordination for Sustainable Pollution–Carbon Performance in Municipal Wastewater Systems: Evidence from Fujian, China

Zhihong Zhang ¹, Chen Cai ¹  and Sicong Lei ^{2,*} 

¹ Department of Environmental Sciences, College of Environmental Science and Engineering, Tongji University, Shanghai 200092, China; 2180044@tongji.edu.cn (Z.Z.); caic@tongji.edu.cn (C.C.)

² Fujian Urban and Rural Planning Design Institute, Fuzhou 350007, China

* Correspondence: raysicong@gmail.com; Tel.: +86-059187986877

Abstract

Municipal wastewater systems are increasingly expected to support sustainable urban water management by improving pollutant removal while limiting carbon burdens, yet the plant–network structure behind system performance remains insufficiently understood. This study assessed nine prefecture-level cities in Fujian, China, during 2015–2024 using pollution–carbon accounting with Monte Carlo uncertainty analysis, a linked dual-subsystem network SBM model, a Global Malmquist–Luenberger (GML) index, and second-stage fractional regression. Treated wastewater volume, reclaimed water reuse, and COD removal increased substantially, while net GHG emissions rose from 36.41×10^4 t CO₂-eq in 2015 to 49.84×10^4 t CO₂-eq in 2024. However, net GHG intensity declined per treated wastewater volume and per COD removal, indicating improved carbon intensity despite rising total emissions. Mean overall efficiency was 0.690, with lower network-side than plant-side efficiency (0.558 versus 0.892), identifying collection and conveyance as the main bottlenecks. Dynamic performance was broadly stable (mean GML = 1.001). Fractional regression showed that sewer density was negatively associated with overall and network-side efficiency, especially under higher hydraulic loading. Wastewater-system improvement should therefore shift from capacity expansion alone toward coordinated plant–network optimization to support sustainable wastewater management.

Keywords: municipal wastewater system; plant–network coordination; pollution–carbon synergy; network SBM; Global Malmquist–Luenberger index; fractional regression; greenhouse-gas emissions; sustainable wastewater management



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1. Introduction

Municipal wastewater systems are essential infrastructure for urban water-quality protection, public health, and resource recovery. Over recent decades, the expansion of wastewater treatment capacity and the tightening of discharge standards have substantially improved pollutant removal in many regions. However, wastewater treatment is also energy- and carbon-intensive. Higher treatment volumes, stricter effluent requirements, aeration demand, sludge handling, and process-related CH₄ and N₂O emissions may increase the carbon burden of wastewater services [1–3]. As a result, wastewater systems can no longer be evaluated only by treatment coverage or pollutant-removal performance; they also need to be assessed in terms of their pollution–carbon coordination.

This issue is particularly relevant in China, where municipal wastewater infrastructure has expanded rapidly under the dual pressures of water-environment improvement and carbon mitigation. Recent studies have shown that stricter wastewater treatment targets may improve effluent quality while increasing short-term carbon-emission pressure [3], and that wastewater-sector benchmarking increasingly needs to integrate both pollution reduction and carbon-emission reduction [4,5]. These findings point to a central challenge: improving wastewater treatment performance does not automatically lead to lower-carbon system operation.

In response to this shift, wastewater-efficiency studies have increasingly expanded their assessment boundary from conventional treatment performance to broader environmental and carbon-related performance. Earlier DEA-based studies mainly examined whether wastewater treatment plants (WWTPs) could use inputs such as capital, energy, and operating resources efficiently to achieve treatment outputs, while also identifying the importance of plant scale, treatment technology, energy consumption, operating conditions, and external environment [6–8]. More recent studies have incorporated undesirable outputs, carbon emissions, and dynamic productivity change into wastewater-system assessment [9–14]. This development reflects an important shift from single-purpose treatment evaluation toward broader environmental-performance assessment.

Nevertheless, most existing studies still provide limited insight into where inefficiency occurs within the wastewater system. Wastewater treatment is often evaluated either at the plant level or as an aggregated city-level production process. Such approaches are useful for benchmarking overall performance, but they make it difficult to distinguish whether inefficiency arises from upstream collection and conveyance, downstream treatment conversion, or the coordination between the two. This distinction is important because treatment plants can only perform effectively when the sewer network collects and delivers wastewater in a stable and coordinated way. Recent research has also emphasized that sewer networks are not passive conveyance channels, but are connected to urban hydrodynamics, infrastructure conditions, water quality, and greenhouse-gas generation [15]. A plant-only or black-box perspective may therefore overlook an important source of wastewater-system inefficiency.

Network DEA provides a useful way to address this limitation because it represents the internal structure of a production system rather than treating the system as a single black box [16,17]. For municipal wastewater systems, this logic is especially appropriate. The upstream subsystem can represent wastewater collection and conveyance, while the downstream subsystem can represent treatment conversion, pollutant removal, sludge generation, reclaimed-water reuse, and carbon emissions. Such a linked perspective can help identify whether inefficiency arises mainly from the network side, the plant side, or the coordination between them.

To address this gap, this study develops an integrated plant–network assessment of municipal wastewater systems in nine prefecture-level cities in Fujian Province, China, during 2015–2024. The analysis first estimates annual COD removal and net greenhouse-gas emissions to characterize pollution–carbon outcomes. It then applies a linked dual-subsystem network SBM model to distinguish overall efficiency, network-side efficiency, and plant-side efficiency. A Global Malmquist–Luenberger index is used to examine dynamic performance changes, and fractional regression models are used to explore the factors associated with efficiency differences.

Against this background, this study extends previous wastewater-efficiency research in three respects. First, it represents municipal wastewater systems as a linked plant–network process rather than as isolated WWTPs or black-box city-level units, allowing collection–conveyance and treatment–conversion performance to be distinguished within the same framework. Second, it embeds pollution abatement and carbon burden in a

common assessment boundary by considering COD removal, dry sludge production, net GHG emissions, and the reclaimed-water substitution offset. Third, by combining static efficiency, dynamic productivity change, and second-stage regression, it identifies not only whether pollution–carbon performance changed over time, but also which subsystem formed the main bottleneck and which city-level conditions were associated with efficiency differences. By linking wastewater collection, treatment conversion, pollutant removal, and carbon emissions, this framework provides a sustainability-oriented basis for assessing and monitoring municipal wastewater systems.

2. Materials and Methods

2.1. Study Area and Analytical Unit

This study focused on nine prefecture-level city wastewater systems in Fujian Province, China, over 2015–2024. Fujian was selected because its municipal wastewater infrastructure has expanded continuously in recent years, including sewer-network construction, centralized treatment capacity, reclaimed-water reuse, and discharge-standard upgrading. The province also contains cities with different wastewater-system scales, sewer-network conditions, treatment-capacity structures, and hydraulic loading levels, making it suitable for examining plant–network coordination at the city level.

The analytical unit was the city-year observation, resulting in a balanced panel of 90 observations. The analytical boundary followed the operational flow of the municipal wastewater system, from sewer collection and conveyance to centralized wastewater treatment, pollutant removal, sludge generation, reclaimed-water reuse, and greenhouse-gas emissions. Decentralized rural treatment facilities, industrial wastewater treated independently outside municipal WWTPs, and receiving-water processes after discharge were outside the analytical boundary. The analytical boundary is illustrated in Figure S1.

City labels were anonymized as City-A to City-I according to the data-use requirements of the data providers. These labels are used consistently throughout the manuscript, figures, and Supplementary Materials. The city-level wastewater-system profiles are summarized in Table 1.

Table 1. Basic wastewater-system profiles of the nine anonymized study cities, 2015–2024.

City	Average Annual Treated Wastewater Volume (10 ⁴ m ³ yr ^{−1})	Average Design Treatment Capacity (10 ⁴ m ³ d ^{−1})	Average Sewer Density in Built Districts (km ^{−2})	Average Hydraulic Load Rate (%)	Average Share of High-Standard Treatment Capacity (%)
City-A	32,861.13 ± 4730.87	129.45 ± 13.70	10.83 ± 0.75	76.54 ± 12.42	100.00 ± 0.00
City-B	41,001.60 ± 12,305.38	91.50 ± 0.00	9.73 ± 0.53	84.47 ± 26.05	100.00 ± 0.00
City-C	8122.34 ± 1471.51	20.75 ± 1.31	13.13 ± 0.97	81.79 ± 16.39	100.00 ± 0.00
City-D	2892.32 ± 835.33	24.55 ± 5.29	7.54 ± 0.28	81.43 ± 9.11	80.29 ± 29.48
City-E	10,508.53 ± 1022.28	83.75 ± 3.86	8.46 ± 0.57	85.47 ± 4.08	100.00 ± 0.00
City-F	7363.09 ± 3446.30	64.60 ± 14.84	14.58 ± 1.20	77.69 ± 31.12	100.00 ± 0.00
City-G	2806.05 ± 437.65	20.30 ± 0.97	7.58 ± 0.50	68.28 ± 10.45	25.37 ± 13.22
City-H	6188.54 ± 530.86	32.70 ± 1.28	8.07 ± 0.66	93.12 ± 6.92	10.81 ± 15.92
City-I	2719.67 ± 1355.25	21.00 ± 6.29	8.98 ± 0.50	79.30 ± 22.56	95.87 ± 9.46

Note: Values are reported as mean ± standard deviation over 2015–2024. City names were anonymized according to data-use requirements.

Rather than evaluating wastewater treatment plants as isolated facilities, this study examined how upstream collection and conveyance conditions and downstream treatment performance jointly shape pollution–carbon performance at the city level.

2.2. Data Sources and Aggregation

Plant-level annual operational records for 2015–2024 were collected for municipal wastewater treatment plants in the nine cities. These records included treated wastewater

volume, design treatment capacity, operating days, electricity consumption, influent and effluent COD and TN concentrations, reclaimed water reuse, and sludge output. City-level infrastructure and socioeconomic data were compiled from official statistical yearbooks, urban construction yearbooks, and municipal water-sector bulletins.

The plant-level records were screened for missing, inconsistent, and clearly abnormal values before aggregation. City-year indicators were then constructed by summing flow variables and by calculating treated-wastewater-weighted averages for water-quality and intensity variables. Hydraulic load rate was recalculated using cleaned treated wastewater volume, design capacity, and operating days to ensure consistency across cities and years. Detailed data-screening rules and variable construction procedures are provided in the Supplementary Materials.

The data used in the main-text figures were derived from the cleaned and anonymized city-year panel and the corresponding accounting and model outputs described in Sections 2.3–2.7. Provincial trend figures were based on aggregated treatment, reuse, water-quality, sludge, electricity, and pollution–carbon accounting data, whereas efficiency, productivity, and regression-prediction figures were based on the corresponding model outputs.

2.3. Annual Pollution–Carbon Accounting

Annual COD removal for city i in year t was calculated as:

$$CODR_{it} = Q_{it} \times (COD_{it}^{in} - COD_{it}^{out}) \times 10^{-3}, \quad (1)$$

where Q_{it} is annual treated wastewater volume, and COD_{it}^{in} and COD_{it}^{out} are the treated-wastewater-weighted influent and effluent COD concentrations, respectively.

Annual net greenhouse-gas emissions were calculated as the sum of direct process-related emissions and indirect electricity-related emissions, minus the reclaimed-water substitution offset:

$$NGHG_{it} = GHG_{it}^{direct} + GHG_{it}^{elec} - GHG_{it}^{reuse}, \quad (2)$$

Direct emissions included methane and nitrous oxide generated during wastewater treatment. Their estimation followed Intergovernmental Panel on Climate Change (IPCC) default wastewater-emission methods and standard 100-year global warming potential settings. Indirect emissions were calculated from annual electricity consumption and the corresponding yearly grid-emission factor. The reclaimed-water offset represented the avoided carbon burden associated with substituting part of conventional water supply through reclaimed-water use [18].

Thus, the accounting system yielded two core performance indicators for each city-year: annual COD removal as the desirable environmental output and annual net GHG emissions as the carbon burden. These two indicators also served as the basis for the uncertainty analysis and the later efficiency and productivity analysis. The expanded accounting equations, parameter settings, and supplementary assumptions are reported in the Supplementary Materials.

2.4. Monte Carlo Uncertainty Analysis

To assess the robustness of the pollution–carbon accounting results, a Monte Carlo uncertainty analysis was conducted after annual COD removal and net GHG emissions were calculated. Similar approaches have been widely used in wastewater environmental and greenhouse-gas studies to test whether the main results remain stable under reasonable parameter changes [19,20].

The simulation focused on key accounting parameters rather than annual activity data. Specifically, influent and effluent COD and TN concentrations, electricity-related emission assumptions, and reclaimed-water substitution parameters were perturbed within predefined distributions and ranges, while observed annual activity data, such as treated wastewater volume and reclaimed water reuse, were kept fixed. This design was adopted because the activity data represented observed city-year operating scales compiled from administrative plant records. Perturbing them would have mixed accounting-parameter uncertainty with hypothetical scenario changes in treatment scale and reuse volume. Therefore, the Monte Carlo analysis estimated conditional uncertainty around observed activity levels rather than full scenario uncertainty. A total of 5000 simulations were conducted for each city-year observation.

The resulting distributions were used to derive uncertainty ranges for annual COD removal and net GHG emissions and to assess whether the main temporal and spatial patterns remained stable under repeated perturbation. The detailed distribution settings, parameter ranges, and supplementary results are reported in the Supplementary Materials.

The uncertainty intervals for the carbon-intensity indicators were derived by normalizing the Monte Carlo-based annual net GHG estimates by treated wastewater volume and COD removal. Because annual activity data were kept fixed in the simulation, these intervals mainly reflect uncertainty in accounting parameters and water-quality inputs.

2.5. Linked Dual-Subsystem Network SBM Model

To identify where inefficiency arises within the municipal wastewater system, this study employed a linked dual-subsystem network slack-based measure (SBM) model with undesirable outputs. This modeling strategy follows the network DEA/SBM literature that represents linked internal processes within a unified production system [16,17].

The model distinguishes between an upstream network-side subsystem and a downstream plant-side subsystem. The network-side subsystem represents wastewater collection and conveyance. Its inputs were three-year average drainage fixed-asset investment and sewer-network length, and its output was annual treated wastewater volume. The plant-side subsystem represents treatment and pollution–carbon conversion. Its inputs were treatment capacity and influent COD load. Its desirable output was annual COD removal, while its undesirable outputs were annual net GHG emissions and dry sludge production. The two subsystems were linked by annual treated wastewater volume, which served as the inter-subsystem link variable.

The use of three-year average drainage fixed-asset investment, rather than annual investment, was intended to reduce the influence of short-term construction fluctuations on the network-side efficiency score. Influent COD load was included in the plant-side subsystem to account for differences in incoming pollution burden across city-year observations. Reclaimed water reuse was not specified as an independent desirable output in the efficiency model. Instead, its carbon-mitigation effect was incorporated through annual net GHG emissions, from which the reclaimed-water substitution offset had already been subtracted.

The overall efficiency of decision-making unit j can be expressed in non-radial SBM form as:

$$\rho_j = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_{ij}}{1 + \frac{1}{r+s} \left(\sum_{r=1}^r s_r^g / y_{rj}^g + \sum_{k=1}^s s_k^b / y_{kj}^b \right)}, \quad (3)$$

where s^- denotes input slacks, s^g denotes desirable-output shortfalls, and s^b denotes undesirable-output excesses. A higher score indicates better performance under the given input–output setting.

Based on this linked structure, the model generated three efficiency measures for each city-year observation: overall efficiency, network-side efficiency, and plant-side efficiency. The two subsystem scores were derived from the same linked network structure under the corresponding subsystem-specific input–output setting. The full model specification, linkage constraints, subsystem-specific score definitions, and notation are provided in the Supplementary Materials.

2.6. Dynamic Productivity Analysis

To assess intertemporal changes in pollution–carbon productivity during 2015–2024, a Global Malmquist–Luenberger (GML) productivity index was further employed. The GML framework is suitable for this setting because it accommodates both desirable and undesirable outputs and allows productivity change to be decomposed into efficiency change (EC) and technical change (TC) [21,22].

The GML index between period t and $t + 1$ can be written as:

$$GML_{t+1}^t = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})}, \quad (4)$$

where $D^G(\cdot)$ denotes the global directional distance function, x represents inputs, y desirable outputs, and b undesirable outputs.

Following the standard decomposition, the GML index was separated into efficiency change and technical change:

$$GML = EC \times TC, \quad (5)$$

A GML value greater than 1 indicates productivity improvement, whereas a value below 1 indicates productivity decline. EC describes whether a city-year observation moved closer to or farther from the contemporaneous best-performing observations, whereas TC describes whether the overall best-performing benchmark became more or less favorable over time. The detailed decomposition formulas are presented in the Supplementary Materials.

2.7. Fractional Regression for Factors Associated with Efficiency

To examine the factors associated with wastewater-system efficiency, second-stage regression models were estimated separately for overall efficiency, network-side efficiency, and plant-side efficiency. The dependent variables were the efficiency scores derived from the linked dual-subsystem network SBM model.

Because the efficiency scores are bounded within the unit interval, the second-stage analysis was implemented using fractional regression models with a logit link, which are suitable for proportional or fractional response variables [23,24]. The regression results are interpreted as conditional associations rather than causal effects, because unobserved city-level factors, such as fiscal capacity, terrain, legacy sewer conditions, and unmeasured network quality, may also affect wastewater-system efficiency.

The baseline explanatory variables included sewer density in built districts, centralized treatment rate, per capita daily water use, hydraulic load rate, and the share of treatment capacity meeting China's Grade 1A or higher discharge standard (share of high-standard treatment capacity). Hydraulic load rate refers to the hydraulic utilization of treatment capacity, rather than pollutant loading intensity. Extended models additionally controlled for per capita GDP, population density, and annual precipitation.

The baseline specification can be written as:

$$E(\theta_{it} | X_{it}, Z_{it}) = G(\alpha + \beta X_{it} + \gamma Z_{it} + \delta_t), \quad (6)$$

where θ_{it} denotes one of the three efficiency measures for city i in year t , $G(\cdot)$ is the logistic response function, X_{it} is the vector of plant–network and treatment–structure variables, Z_{it} is the vector of additional controls, and δ_t represents year effects.

To examine whether the association between sewer expansion and efficiency differed under different system-utilization conditions, an interaction specification was also estimated. The interaction term was constructed as the product of sewer density and hydraulic load rate for each city-year observation. Hydraulic load rate was expressed in percentage units in the regression dataset. The interaction specification can be written as:

$$E(\theta_{it} | X_{it}, Z_{it}) = G(\alpha + \beta_1 SD_{it} + \beta_2 HLR_{it} + \beta_3 SD_{it} \times HLR_{it} + \beta X'_{it} + \delta_t), \quad (7)$$

where SD_{it} denotes sewer density and HLR_{it} denotes hydraulic load rate. In this specification, the main-effect coefficients of sewer density and hydraulic load rate should be interpreted conditionally because of the interaction term. Therefore, the interpretation focuses on the interaction coefficient and the corresponding predicted efficiency curves.

For graphical presentation of the interaction results, marginal predicted efficiency values were calculated over the observed range of sewer density under two representative hydraulic load conditions. The lower and higher hydraulic load conditions were defined as the lower-quartile and upper-quartile values of hydraulic load rate, respectively. Other explanatory variables were held at their sample means, and year effects were averaged over the observed sample distribution. The 95% confidence intervals in the interaction plots were derived from the estimated variance–covariance matrix of the fractional regression coefficients and represent uncertainty in the model-predicted mean efficiency. Robust standard errors were used in all regression specifications.

Static linked dual-subsystem network SBM efficiency scores were estimated using DeaRun (version 3.2.0.5; independently developed DEA software, China). The GML decomposition and second-stage fractional regression analyses were implemented using custom scripts in Python (version 3.12.13; Python Software Foundation, Wilmington, DE, USA). Final figures were prepared using MATLAB R2024b (version 24.2.0.2712019; The MathWorks, Inc., Natick, MA, USA).

3. Results

3.1. Provincial Trends in Wastewater Treatment, Pollution Abatement, Carbon Emissions, and Carbon Intensity

Figure 1 shows the provincial annual trends in wastewater treatment scale, reclaimed water reuse, COD removal, net greenhouse gas (GHG) emissions, and carbon-intensity indicators in Fujian during 2015–2024.

As shown in Figure 1a, the total volume of treated wastewater increased steadily over the study period, from $8.39 \times 10^8 \text{ m}^3$ in 2015 to $15.23 \times 10^8 \text{ m}^3$ in 2024. This indicates a clear expansion of municipal wastewater treatment services in Fujian over the past decade. Figure 1b shows that reclaimed water reuse also rose markedly, from $0.01 \times 10^8 \text{ m}^3$ in 2015 to $5.09 \times 10^8 \text{ m}^3$ in 2024. The increase became more evident after 2017, suggesting that water reuse expanded along with the growth of the treatment system.

At the same time, the pollution abatement outcome improved in absolute terms. As shown in Figure 1c, annual COD removal increased from $15.55 \times 10^4 \text{ t}$ in 2015 to $28.45 \times 10^4 \text{ t}$ in 2024. The overall trend was upward, although the year-to-year increase was not completely even. The shaded band in Figure 1c represents the Monte Carlo-based uncertainty interval and shows that uncertainty remained present around the annual estimates, but the upward pattern was still clear across the full study period.

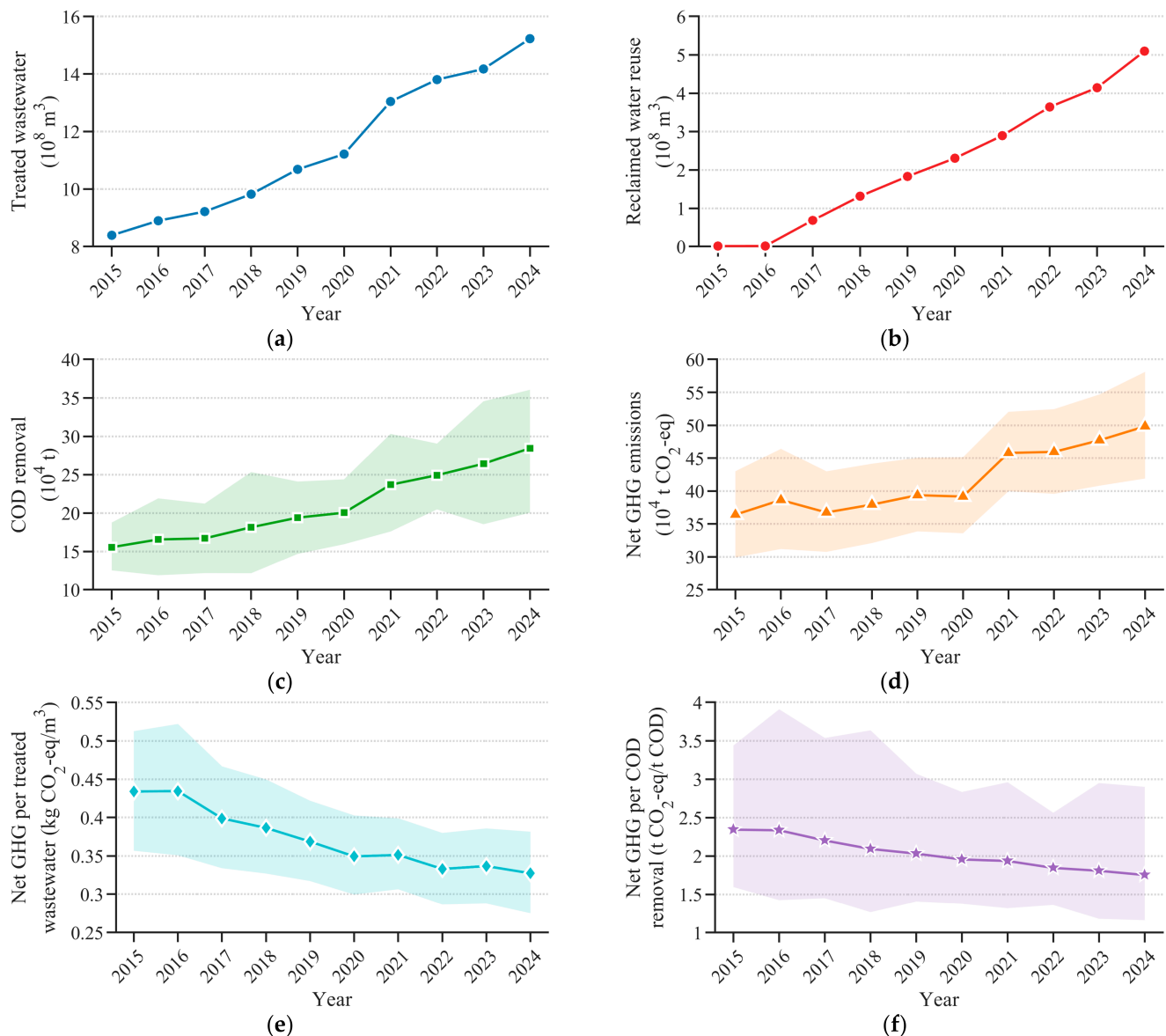


Figure 1. Provincial annual trends in wastewater treatment scale, reclaimed water reuse, pollution abatement, carbon emissions, and carbon intensity in Fujian during 2015–2024: (a) total annual volume of treated wastewater; (b) total annual volume of reclaimed water reuse; (c) annual provincial COD removal; (d) annual provincial net greenhouse gas (GHG) emissions; (e) net GHG emissions per unit of treated wastewater volume; and (f) net GHG emissions per unit of COD removal. The solid lines show annual point estimates. The shaded bands in panels (c–f) indicate Monte Carlo-based uncertainty intervals derived from the pollution–carbon accounting framework. Because annual activity data were kept fixed in the Monte Carlo analysis, these bands mainly reflect uncertainty in accounting parameters and water-quality inputs rather than the full uncertainty of all activity data.

Figure 1d shows a similar upward trend in annual net GHG emissions. Net GHG emissions increased from $36.41 \times 10^4 \text{ t CO}_2\text{-eq}$ in 2015 to $49.84 \times 10^4 \text{ t CO}_2\text{-eq}$ in 2024. Compared with COD removal, the uncertainty band for net GHG emissions was narrower, but the direction of change was also consistently upward. Taken together, Figure 1c,d show that stronger pollution removal at the provincial level was accompanied by a higher overall carbon burden.

To further distinguish scale effects from intensity changes, Figure 1e,f show net GHG emissions normalized by treated wastewater volume and COD removal, respectively. Net GHG emissions per unit treated wastewater declined from $0.434 \text{ kg CO}_2\text{-eq m}^{-3}$ in 2015

to 0.327 kg CO₂-eq m⁻³ in 2024. Similarly, net GHG emissions per unit COD removal decreased from 2.342 t CO₂-eq t⁻¹ COD in 2015 to 1.752 t CO₂-eq t⁻¹ COD in 2024. These results indicate that the carbon burden per unit service output declined over time, even though absolute net GHG emissions increased. Therefore, the rising total carbon burden was mainly associated with system expansion rather than deterioration in carbon intensity.

The city-level results shown in Figures S2 and S3 further indicate that the provincial pattern was not driven by only one year or one city. Most cities showed an overall increase in COD removal and net GHG emissions over time, although the magnitude differed substantially across cities. Table 1 summarizes the basic characteristics of city-level wastewater systems. Read together, Figures S2 and S3 and Table 1 show clear differences in treatment scale and operating conditions across cities. For example, average annual treated wastewater volume ranged from $2719.67 \times 10^4 \text{ m}^3 \text{ yr}^{-1}$ in City-I to $41,001.60 \times 10^4 \text{ m}^3 \text{ yr}^{-1}$ in City-B, while the average hydraulic load rate ranged from 68.28% in City-G to 93.12% in City-H. In general, larger systems contributed more to total COD removal and total net GHG emissions, whereas smaller systems remained lower in absolute terms across most years. Overall, the results in Figures 1, S2 and S3 show a clear provincial pattern during 2015–2024. The wastewater system expanded continuously, reclaimed water reuse increased substantially, and COD removal improved. Absolute net GHG emissions also rose, but the carbon burden per unit treated wastewater and per unit COD removal declined. This indicates that the provincial system showed improvement in carbon intensity, although scale expansion continued to increase the total carbon burden.

3.2. Static Efficiency of the Wastewater System

The static efficiency results of the city-level wastewater systems are summarized in Table 2, and the spatial and temporal patterns are shown in Figures 2 and S4.

Table 2. Summary statistics of static efficiency scores for the city-level wastewater systems in Fujian during 2015–2024.

Metric	Mean	SD	Min	Max
Overall efficiency	0.690	0.148	0.475	1.000
Network-side efficiency	0.558	0.233	0.182	1.000
Plant-side efficiency	0.892	0.111	0.626	1.000

Note: The table reports the mean standard deviation (SD), minimum, and maximum values of the overall efficiency, network-side efficiency, and plant-side efficiency scores based on 90 city-year observations for the nine cities. Efficiency scores were estimated using the linked dual-subsystem network SBM model.

Overall, the wastewater systems showed a moderate level of static efficiency during 2015–2024. The mean overall efficiency was 0.690, indicating that the integrated performance of the wastewater systems still had room for improvement. When the system was further divided into the network-side and plant-side subsystems, clear differences were observed. The mean network-side efficiency was 0.558, whereas the mean plant-side efficiency reached 0.892. This result indicates that the main bottleneck was located in the network-side subsystem rather than in the plant-side subsystem.

Figure 2a shows the city-year distribution of overall efficiency. Considerable heterogeneity can be observed across both cities and years. Some city-year observations approached the efficiency frontier, whereas others remained at relatively low levels. In general, the spread across cities was more evident than the fluctuation within individual cities, suggesting that cross-city differences were an important feature of the static efficiency results.

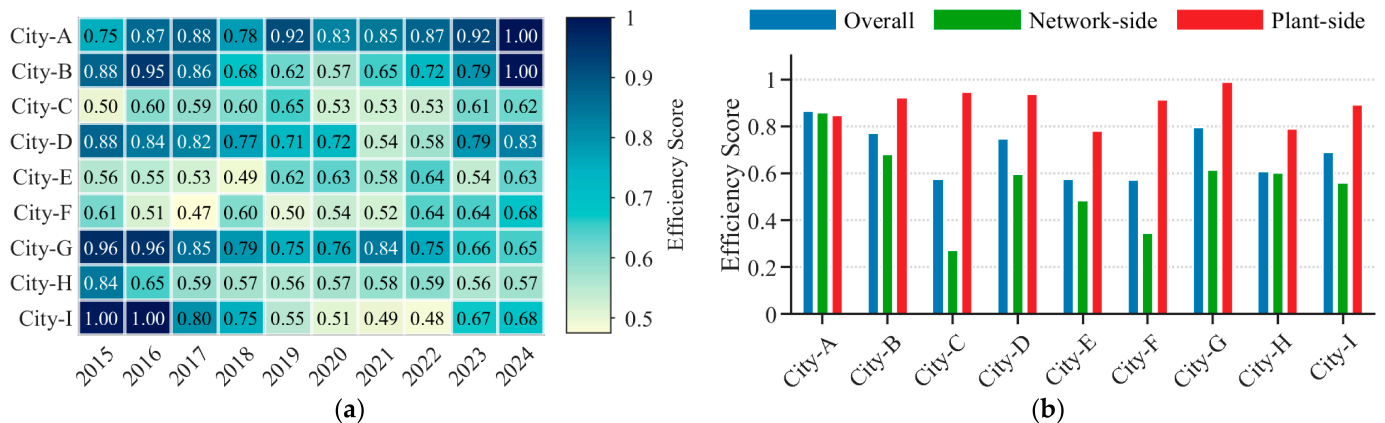


Figure 2. Static efficiency patterns of the city-level wastewater systems in Fujian during 2015–2024: (a) The city-year distribution of overall efficiency scores for the nine cities (City-A to City-I). The color scale represents the magnitude of overall efficiency. (b) Compares the mean efficiency scores of the overall system, the network-side subsystem, and the plant-side subsystem for each city over 2015–2024. Efficiency scores were estimated using the linked dual-subsystem network SBM model. In the network-side subsystem, three-year average drainage fixed-asset investment and sewer length were treated as inputs, and treated wastewater volume was used as the link variable. In the plant-side subsystem, treatment capacity and influent COD load were treated as inputs, COD removal was specified as the desirable output, and net greenhouse gas (GHG) emissions and dry sludge production were specified as undesirable outputs.

Figure 2b further compares the mean efficiency values of each city. City-A showed the highest mean overall efficiency (0.865), followed by City-G (0.797) and City-B (0.772). At the lower end, City-F (0.572), City-C (0.576), and City-E (0.576) had the lowest mean overall efficiency values. The subsystem results also differed across cities. For example, City-A showed relatively high values in both the network-side and plant-side subsystems, while several cities with lower overall efficiency were mainly constrained by weak network-side performance. In contrast, plant-side efficiency was generally high in most cities, and the differences across cities were narrower than those observed for the network-side subsystem.

The annual mean trends presented in Figure S4 show that plant-side efficiency remained consistently higher than both overall efficiency and network-side efficiency throughout the study period. By comparison, the temporal variation in overall efficiency broadly followed the variation in network-side efficiency, further indicating the stronger influence of the network-side subsystem on the overall system performance.

Taken together, the results show that the static efficiency of the wastewater systems varied substantially across cities, but the main pattern was consistent. The network-side subsystem remained the weaker part of the system, whereas the plant-side subsystem generally performed better and was closer to the efficiency frontier.

3.3. Dynamic Changes in the Pollution–Carbon Performance of the Wastewater System

To further examine whether the pollution–carbon performance of the municipal wastewater systems changed over time, a Global Malmquist–Luenberger (GML) index was estimated for adjacent-year transitions during 2015–2024. In this study, the GML index was further separated into two parts: efficiency change (EC) and technical change (TC). A value greater than 1 indicates improvement, whereas a value below 1 indicates decline. Here, EC is used to describe whether a city-year observation moved closer to or farther from the contemporaneous best-performing observations, while TC is used to describe whether the overall best-performing benchmark became more favorable or less favorable over time.

The summary statistics are reported in Table 3. Across all city-year transitions, the mean GML value was 1.001, indicating that the overall pollution–carbon performance changed little during the study period, with only a slight net improvement on average. The mean EC and TC values were also both close to 1 (1.000 and 1.001, respectively), suggesting that neither the relative performance of individual cities nor the best-performing benchmark changed sharply at the panel level. However, some variation still existed across city-year transitions, with GML ranging from 0.896 to 1.170.

Table 3. Summary statistics of the Global Malmquist–Luenberger (GML) index and its two components for the nine-city panel.

Metric	Mean	SD	Min	Max
GML	1.001	0.025	0.896	1.170
EC	1.000	0.021	0.881	1.135
TC	1.001	0.026	0.877	1.170

Note: The table reports the mean, standard deviation, minimum, and maximum values of GML, EC, and TC for all adjacent-year transitions from 2015/2016 to 2023–2024. Values greater than 1 indicate improvement in the corresponding index, whereas values below 1 indicate decline.

The annual mean results are shown in Figure 3. Overall, the dynamic pattern remained close to 1 in most years, indicating that year-to-year changes were generally modest. The annual mean GML value was 1.000 in 2016, 0.997 in 2017, 1.000 in 2018, and then declined to 0.995 in 2019 and 0.989 in 2020. This suggests that the pollution–carbon performance weakened slightly during the late 2010s and reached its lowest annual mean level in 2020. It then recovered to 0.998 in 2021, stayed near 1 in 2022 (1.001), increased more visibly in 2023 (1.026), and returned to a near-stable level in 2024 (1.001). Taken together, these results indicate that system performance did not improve continuously over time, but instead fluctuated around a broadly stable level.

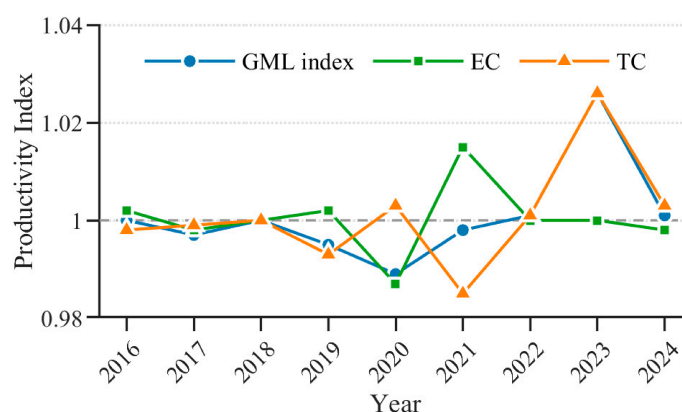


Figure 3. Annual mean Global Malmquist–Luenberger (GML) index and its two components for the nine municipal wastewater systems in Fujian during 2015–2024. The value shown for each year represents the change from the previous year to that year. Values greater than 1 indicate improvement, whereas values below 1 indicate decline. EC denotes changes in the relative performance of city-year observations, and TC denotes changes in the overall best-performing benchmark. The horizontal dashed line indicates the stability threshold of 1.0.

The two component series provide additional information on the source of these changes. In 2020, the decline in GML was mainly associated with a lower EC value (0.987), while TC remained slightly above 1 (1.003). This suggests that the weaker performance in that year was more related to a temporary decline in the relative performance of some cities than to a deterioration in the overall benchmark level. In 2021, EC rose to 1.015 while TC fell to 0.985, indicating that improved relative performance partly offset less

favorable benchmark conditions. The more visible increase in 2023 was mainly driven by TC (1.026) rather than EC (1.000), suggesting that the improvement in that year was more closely related to a better best-performing benchmark than to additional gains in the relative performance of individual cities.

The city-year heatmap in Figure S5 provides further detail on spatial and temporal heterogeneity. Most city-year transitions remained close to 1, and departures above or below 1 were usually temporary rather than persistent. In other words, the dynamic pattern was characterized more by moderate short-term fluctuation than by strong or lasting divergence across cities. This is consistent with the relatively narrow range of city-level mean values, indicating that dynamic differences across cities were present but not pronounced.

Overall, the GML results suggest that the municipal wastewater systems in Fujian showed broadly stable pollution–carbon performance during 2015–2024, with only slight net improvement at the aggregate level. Compared with the clearer cross-city differences observed in the static linked dual-subsystem SBM results, the dynamic analysis reveals a more muted pattern in which year-to-year changes were limited in size and remained close to stability in most years.

3.4. Fractional Regression Analysis of Efficiency Determinants

Second-stage fractional regression models were estimated to examine the factors associated with the efficiency differences identified by the linked dual-subsystem network SBM model. Because the efficiency scores are bounded between 0 and 1, a fractional regression model with a logit link was used. Three specifications were estimated: a baseline model, an extended model with additional socioeconomic and climatic controls, and an interaction model including the term between sewer density and hydraulic load rate.

The main results for overall efficiency are reported in Table 4, while the corresponding subsystem results are provided in Tables S4 and S5. Overall, sewer density was the most stable explanatory variable. In the baseline model, sewer density was negatively associated with overall efficiency, with a coefficient of -0.1067 . This relationship remained in the extended model, where the coefficient was -0.1168 . Both estimates were statistically significant at the 1% level. The same pattern was observed for network-side efficiency in Table S4, where sewer density remained negative and statistically significant in both the baseline and extended specifications. These results indicate that denser sewer networks did not automatically correspond to better wastewater-system performance. Instead, higher sewer density was more often associated with lower efficiency, especially on the network side.

The results for centralized treatment rate and hydraulic load rate were less stable across specifications. In the baseline model, centralized treatment rate was positively associated with overall efficiency, but this association became weaker after the additional controls were included. For network-side efficiency, centralized treatment rate also showed a positive relationship in the baseline model, but its robustness was limited in the extended specification. By contrast, hydraulic load rate was negatively associated with overall efficiency in both the baseline and extended models. A similar negative association was observed for network-side efficiency in Table S4. This suggests that higher hydraulic loading should not be interpreted simply as better system coordination. In this sample, higher load rates may also reflect greater operating pressure within the collection–treatment system.

Among the additional controls in the extended model, population density showed a positive association with overall efficiency and network-side efficiency. This suggests that more compact urban development may be associated with more efficient wastewater-

system operation. The coefficients for ln GDP per capita and annual precipitation were not stable enough to support strong interpretation in the present sample.

Table 4. Second-stage fractional regression results for overall efficiency.

Variable	Baseline	Extended	Interaction
Sewer density	−0.1067 *** (0.0305)	−0.1168 *** (0.0279)	0.6179 * (0.3182)
Centralized treatment rate	0.0160 * (0.0087)	0.0035 (0.0105)	0.0070 (0.0099)
Per capita daily water use	0.0016 (0.0021)	0.0025 (0.0022)	0.0004 (0.0023)
Hydraulic load rate	−0.0174 * (0.0093)	−0.0205 ** (0.0086)	0.0755 * (0.0424)
High-standard share	0.0043 (0.0027)	0.0015 (0.0029)	0.0039 (0.0026)
ln GDP per capita		−0.3129 (0.5487)	
Population density		0.0001 *** (0.0000)	
Annual precipitation		0.0004 (0.0005)	
Sewer density × hydraulic load rate			−0.0085 ** (0.0037)
N	90	90	90
McFadden pseudo R ²	0.0338	0.0417	0.0382

Note: The dependent variable is the overall efficiency score derived from the linked dual-subsystem network SBM model. Robust standard errors are reported in parentheses. Year effects are included in all specifications. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The interaction model provides a more direct view of plant–network coordination. In Table 4, the coefficient of sewer density × hydraulic load rate was negative for overall efficiency (−0.0085). In Table S4, the same interaction term was also negative for network-side efficiency (−0.0098). These results indicate that the relationship between sewer density and efficiency depended partly on system utilization conditions. As shown in Figure 4a,b, the predicted efficiency curves decline more clearly under higher hydraulic load conditions, especially for network-side efficiency. In other words, sewer-network expansion was less likely to be associated with better performance when the system was already operating under heavier hydraulic loading.

The plant-side regression results in Table S5 were less consistent than the overall and network-side results. This is in line with the static SBM results, which showed that plant-side efficiency was generally higher and varied less across cities than network-side efficiency. Therefore, the second-stage results further support the interpretation that the main differences in wastewater-system performance were more closely related to the network-side subsystem and its coordination with plant utilization than to treatment conversion alone.

Overall, the fractional regression results are consistent with the static efficiency findings. The network-side subsystem was more strongly associated with the explanatory variables than the plant-side subsystem. Sewer density was the most robust negative correlate of efficiency, and the interaction results suggest that the negative association between sewer density and efficiency became stronger under higher hydraulic load conditions. These findings support the view that wastewater-system performance depends not only on expanding sewer infrastructure, but also on whether collection, conveyance, and treatment capacity are effectively coordinated.

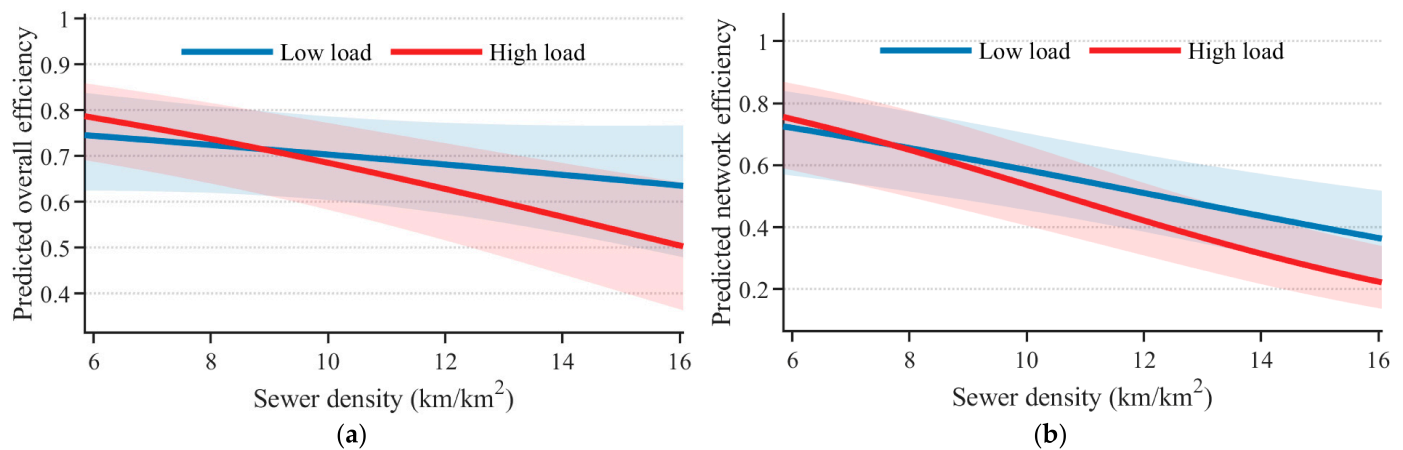


Figure 4. Interaction between sewer density and hydraulic load rate in the second-stage fractional regression model: (a) Predicted overall efficiency over the observed range of sewer density under lower and higher hydraulic load conditions. (b) Predicted network-side efficiency over the observed range of sewer density under lower and higher hydraulic load conditions. The solid lines are marginal predicted efficiency values calculated from the interaction specifications in Tables 4 and S4, rather than simple fitted lines through raw scatter points. Lower and higher hydraulic load conditions correspond to the lower-quartile and upper-quartile values of hydraulic load rate, respectively. The shaded bands indicate 95% confidence intervals for the model-predicted mean efficiency. Other explanatory variables are held at their sample means, and year effects are averaged over the observed sample distribution.

4. Discussion

The results suggest that the main challenge for municipal wastewater systems is not only to expand treatment capacity or increase pollutant removal, but to improve the coordination between wastewater collection, conveyance, treatment, reuse, sludge generation, and carbon emissions. During 2015–2024, Fujian’s wastewater system expanded markedly: treated wastewater volume increased, reclaimed water reuse grew, and annual COD removal improved. Net GHG emissions also increased, although net GHG intensity per treated wastewater volume and per COD removal declined. This indicates that the system became less carbon-intensive per unit service output, but scale expansion still increased the absolute carbon burden. Therefore, the central issue is not whether the system became larger, but whether expansion translated into more efficient pollution–carbon performance.

This finding is consistent with recent studies showing that wastewater treatment increasingly involves a tension between water-quality improvement and carbon mitigation. Yang et al. [3] found that stricter sewage treatment targets in China may improve effluent quality while increasing short-term carbon pressure. Hou et al. [4] also argued that wastewater systems should be assessed through integrated pollution-reduction and carbon-mitigation frameworks. Our results support this view and further show that this tension is not only a treatment-plant issue. It is also shaped by how wastewater is collected, conveyed, and allocated to treatment facilities.

The linked dual-subsystem network SBM results indicate that the plant-side subsystem was generally closer to the efficiency frontier, whereas the network-side subsystem remained the weaker part of the system. This does not mean that treatment plants are unimportant. Rather, it shows that treatment conversion alone cannot explain city-level wastewater-system performance. A city may have relatively strong treatment capacity and pollutant-removal performance, but its overall efficiency can still be constrained if upstream collection and conveyance do not operate effectively. This finding complements WWTP-centered efficiency studies that emphasize plant scale, energy use, treatment technology,

and operating conditions as important drivers of performance [1,6–8]. It also extends Chinese city- and regional-level wastewater efficiency studies by showing that uneven performance may arise from different subsystem constraints rather than from treatment capacity alone [10,11,13].

The city-level results further suggest that plant–network coordination problems are spatially differentiated. Larger systems contributed more to total COD removal and net GHG emissions, but system size did not directly determine efficiency. Some larger systems performed relatively well, while some cities with substantial infrastructure scale still showed weaker integrated efficiency. Conversely, some smaller or medium-sized systems achieved relatively higher efficiency. This indicates that city-level wastewater performance was shaped less by scale alone than by the way sewer-network development, inflow collection, hydraulic loading, treatment utilization, and pollution–carbon conversion were coordinated. The observed heterogeneity should therefore be interpreted as cross-city differences in plant–network coordination, not as a simple coastal–inland or large–small city contrast.

The importance of the network side is consistent with emerging research that treats sewer networks as active components of urban environmental and carbon processes. Chen et al. [15] emphasized that sewer networks are linked to hydrodynamics, infrastructure conditions, and GHG generation rather than serving only as passive conveyance channels. In our study, sewer density was the most stable negative correlate of overall and network-side efficiency. This result should not be interpreted as evidence against sewer construction. Sewer density is a proxy for network scale and potential collection capacity, not a direct measure of wastewater capture quality. It does not directly reveal household connection quality, dry-weather inflow, inflow and infiltration, pipe condition, pump-station performance, or wastewater allocation among treatment plants. The negative association therefore suggests that network expansion alone is insufficient unless it is matched with effective connection, conveyance, and treatment utilization.

The interaction between sewer density and hydraulic load rate further supports this interpretation. A higher hydraulic load rate may indicate better capacity use in some cases, but it may also reflect operating pressure when network expansion, inflow allocation, and treatment capacity are not well coordinated. The negative interaction between sewer density and hydraulic load rate indicates that the association between sewer density and efficiency became more unfavorable under heavier hydraulic loading, especially for network-side efficiency. This suggests that the key issue is not simply low or high plant utilization, but whether collected wastewater can be conveyed and treated under coordinated operating conditions.

The GML results add a temporal perspective. The mean GML value was close to 1, and both EC and TC remained close to 1 on average, indicating that pollution–carbon performance was broadly stable rather than rapidly improving. This is consistent with previous wastewater productivity studies showing that productivity change is often uneven and not necessarily monotonic [6,9,12]. When read together with the static SBM results, the GML findings suggest that Fujian’s wastewater systems did not experience a strong province-wide upgrading trajectory during the study period. Instead, the main issue appears to be a persistent structural imbalance between network-side and plant-side performance.

This study advances the understanding of pollution–carbon synergy in municipal wastewater systems in three respects. First, it shifts the analytical focus from isolated WWTPs to a linked plant–network system, showing why treatment-side performance can be relatively high while overall system efficiency remains constrained. Second, it clarifies that plant–network mismatch should not be reduced to a single symptom such as low load rate. Mismatch can also occur when sewer expansion, wastewater capture, hydraulic

loading, and treatment conversion do not improve together. Third, it shows that cross-city differences in wastewater-system performance may reflect different subsystem constraints, which are difficult to observe in black-box efficiency models.

The practical implication is that wastewater-system planning should move from capacity expansion toward coordinated plant–network optimization. Expanding sewer length and treatment capacity remains necessary, but additional expansion should be evaluated together with actual wastewater capture, hydraulic loading, centralized treatment, energy use, sludge generation, and carbon emissions. For cities with high sewer density but weak network-side efficiency, practical measures to improve sewer efficiency should therefore focus on effective wastewater capture and conveyance rather than network expansion alone. Consistent with evidence that sewer networks are linked to hydrodynamic conditions, infrastructure status, and city-wide environmental dynamics [15], these measures include improving household and industrial connections, reducing infiltration and inflow, rehabilitating leaking or silted pipes, strengthening pump-station operation, separating stormwater and wastewater where mixed inflow is severe, coordinating network extension with treatment-plant capacity, and optimizing inflow allocation among treatment plants.

At the same time, low-carbon wastewater management should focus on reducing the carbon cost of pollutant removal rather than reducing treatment intensity. Relevant actions include energy optimization, aeration control, sludge-management improvement, reduction in direct CH₄ and N₂O emissions, and careful planning of reclaimed-water reuse. This is consistent with water–energy–carbon nexus studies showing that carbon outcomes in WWTPs depend on operating conditions, energy use, influent quality, and process configuration [1,2], and with recent studies calling for integrated pollution-reduction and carbon-mitigation assessment in wastewater systems [4,5,14].

Several limitations should be noted. The analysis is based on nine prefecture-level cities in Fujian during 2015–2024, so the findings are most directly applicable to regions where municipal wastewater infrastructure is still expanding and plant–network coordination remains uneven. The city-year scale is useful for identifying system-level patterns, but it cannot fully reveal physical mechanisms inside sewer networks or treatment plants. Sewer density, centralized treatment rate, and hydraulic load rate are useful city-level proxies, but they cannot directly measure sewer connection rate, dry-weather and wet-weather inflow, combined sewer overflow, infiltration and inflow, pipe condition, pump-station operation, or plant-level inflow distribution. Future research could combine linked DEA models with hydraulic simulation, spatial network analysis, life-cycle carbon accounting, or higher-frequency plant inflow data to move from identifying plant–network coordination problems to diagnosing their physical and operational mechanisms.

Overall, the results indicate that pollution–carbon synergy in municipal wastewater systems depends not only on how much wastewater is treated or how much pollutant is removed, but also on how effectively the collection network and treatment plants operate as an integrated system. The policy message is therefore not to slow wastewater infrastructure development, but to shift the emphasis from expansion alone to coordinated plant–network operation. This shift is essential if municipal wastewater systems are expected to deliver both pollution abatement and carbon mitigation under the dual goals of water-quality improvement and low-carbon transition.

5. Conclusions

This study developed an integrated plant–network assessment framework to evaluate pollution–carbon performance in municipal wastewater systems across nine cities in Fujian during 2015–2024. The results show that wastewater treatment scale, reclaimed water reuse, and COD removal increased substantially over the study period. Treated wastewater

volume increased from $8.39 \times 10^8 \text{ m}^3$ in 2015 to $15.23 \times 10^8 \text{ m}^3$ in 2024, and annual COD removal increased from $15.55 \times 10^4 \text{ t}$ to $28.45 \times 10^4 \text{ t}$. Annual net GHG emissions also increased from $36.41 \times 10^4 \text{ t CO}_2\text{-eq}$ to $49.84 \times 10^4 \text{ t CO}_2\text{-eq}$. However, net GHG intensity declined from 0.434 to 0.327 kg $\text{CO}_2\text{-eq m}^{-3}$ of treated wastewater and from 2.342 to 1.752 t $\text{CO}_2\text{-eq t COD}^{-1}$ removed, indicating improved carbon intensity despite the increase in absolute emissions.

The linked dual-subsystem network SBM results further show that the main efficiency bottleneck was located on the network side rather than the plant side. The mean overall efficiency was 0.690, while network-side efficiency averaged 0.558 and plant-side efficiency averaged 0.892. This suggests that treatment conversion was relatively strong, whereas wastewater collection and conveyance remained the weaker part of the integrated system. The GML results indicate that dynamic pollution–carbon performance was broadly stable, with an average GML value of 1.001 and only slight net improvement during the study period.

The second-stage fractional regression results support this interpretation. Sewer density was negatively associated with overall and network-side efficiency, and the interaction between sewer density and hydraulic load rate suggests that this negative association became stronger under higher hydraulic loading. These findings do not imply that sewer construction is undesirable. Rather, they indicate that network expansion alone is insufficient unless it is matched with effective wastewater capture, conveyance, and treatment utilization.

Overall, the study highlights that improving municipal wastewater systems under pollution-reduction and carbon-mitigation goals requires a shift from capacity expansion alone toward coordinated plant–network optimization. These findings are most applicable to regions where wastewater networks and treatment capacity are still expanding and where plant–network coordination remains uneven. For such regions, the results suggest that sewer-network expansion should be evaluated together with effective wastewater capture, hydraulic loading, treatment-capacity utilization, sludge management, reclaimed-water reuse, and carbon emissions. Future studies should incorporate more direct network-operation indicators, such as sewer connection rates, infiltration and inflow, pipe condition, pump-station operation, plant-level inflow allocation, and higher-frequency influent monitoring. Combining linked efficiency models with hydraulic simulation, spatial network analysis, life-cycle carbon accounting, and additional water-quality indicators such as total dissolved solids would further improve the diagnosis of plant–network mismatch and pollution–carbon trade-offs.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su18147137/s1>, Text S1: Data screening and variable construction; Text S2: Expanded pollution–carbon accounting equations; Text S3: Monte Carlo uncertainty analysis; Text S4: Formal specification of the linked dual-subsystem network SBM model; Text S5: Additional details of GML decomposition; Table S1: Variable definitions, units, and aggregation rules; Table S2: Parameter settings used in annual pollution–carbon accounting; Table S3: Distribution settings and parameter ranges used in the Monte Carlo simulation; Table S4: Second-stage fractional regression results for network-side efficiency; Table S5: Second-stage fractional regression results for plant-side efficiency; Figure S1: Analytical boundary and variable setting of the linked dual-subsystem wastewater-system assessment. Figure S2: City-level annual trends in COD removal in Fujian during 2015–2024; Figure S3: City-level annual trends in net greenhouse-gas emissions in Fujian during 2015–2024; Figure S4: Annual mean static efficiency scores of the city-level wastewater systems in Fujian during 2015–2024; Figure S5: City-year heatmap of the Global Malmquist–Luenberger index for the nine municipal wastewater systems.

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Abbreviations

The following abbreviations are used in this manuscript:

SBM	Slack-based measure
DEA	Data envelopment analysis
GML	Global Malmquist–Luenberger
EC	Efficiency change
TC	Technical change
COD	Chemical oxygen demand
GHG	Greenhouse gas
WWTPs	Wastewater treatment plants
SI	Supplementary Information
IPCC	Intergovernmental Panel on Climate Change
CH ₄	Methane
N ₂ O	Nitrous oxide
CO ₂ -eq	Carbon dioxide equivalent

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