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GREEN DEVELOPMENT EFFICIENCY OF COLD CHAIN LOGISTICS IN THE YANGTZE RIVER ECONOMIC BELT: EVIDENCE FROM A SUSTAINABILITY ORIENTED PERSPECTIVE

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Abstract: The sustainable transformation of cold chain logistics in China's Yangtze River Economic Belt (YREB) plays a pivotal role in fostering the broader national transition toward sustainability. Anchored in the principles of sustainable development, this study employs the super-efficiency slack-based measure and the global Malmquist-Luenberger index to evaluate both the static and dynamic green development efficiency of cold chain logistics across 11 provinces and municipalities within the YREB from 2013 to 2023. Moreover, spatial disparities are investigated through the Dagum Gini coefficient to uncover the regional sustainability gaps. The findings reveal that: (1) Although the overall static green efficiency of cold chain logistics in the YREB remains moderate, total-factor productivity demonstrates a steadily rising trend, reflecting a progressive shift toward sustainable operational performance. (2) Both technical efficiency and technological progress jointly drive this advancement, with technological progress exerting a more pronounced influence on the realization of sustainable efficiency gains. (3) Significant regional disparities persist, exhibiting a nonlinear pattern distinguished by a primary decrease succeeded by subsequent recovery. In response, the study proposes targeted strategies to optimize the allocation of sustainable resource factors, enhance input–output efficiency, implement differentiated regional pathways, and accelerate the sustainable and green development of cold chain logistics within the YREB.
Keywords: Yangtze River Economic Belt; Cold chain logistics; Green development; Super-efficiency slack-based measure; Sustainable development

1 INTRODUCTION

Within the framework of worldwide climate shifts, reaching carbon peak and carbon neutrality represents a shared objective for the global community [1]. The majority of industrialized nations have established carbon-neutrality deadlines following the attainment of carbon peak [2]. As the planet's most populous developing nation, China confronts the dual pressure of advancing economic progress and curbing carbon emissions. On one side, China must ensure continuous economic expansion; on the other side, being the globe's top emitter of carbon dioxide, China targets attaining carbon peak by 2030 and carbon achieve carbon neutrality before 2060.

In contrast to industrialized nations, China's decarbonization journey exhibits notable intricacy and distinctiveness. This is mainly reflected in the following multidimensional nonequilibrium characteristics: uneven regional economic development, differences in green technology innovation capabilities, obvious regional differentiation in carbon-emission levels, and the uneven spatial distribution of emission-reduction potential [3]. These factors are intertwined and together constitute the real dilemma of emission-reduction policy formulation, creating high requirements for the design of differentiated policies [4].

Considering its substantial energy use and considerable carbon output, cold chain logistics assumes a pivotal function in fulfilling emission-cutting targets [5]. In contrast to conventional logistics, cold chain transportation demands the uninterrupted use of a substantial quantity originating from fossil-derived fuel or grid-sourced electricity to preserve a steady chilled-environment condition, which guarantees the integrity and safety of shipped goods. Despite the considerable growth prospects of China's cold chain logistics sector, it continues to encounter challenges including suboptimal operational performance, inconsistent service standards, and uneven regional advancement [6]. The "14th Five-Year Blueprint for Refrigerated Logistics Advancement," released by the State Council, underscores the immediacy of enhancing the functional performance of refrigerated logistics and cutting down discharges to realize superior-grade growth [7]. The eco-friendly advancement degree of cold chain logistics immediately influences resource employment productivity, discharge-reduction capability, and the realization of territorial sustainability objectives.

Being a pivotal strategic advancement zone, the Yangtze River Economic Belt (YREB) spans primary physical zones, encompasses 11 state-level administrative territories, and constitutes over 40% of China's aggregate financial production. It is neither a critical economic expansion driver nor is it an essential environmental safeguard defense [8]. Nonetheless, the green development of cold chain logistics (GDCCL) in this area exhibits marked divergences: the downstream areas have spearheaded achieving sustainable metamorphosis with their technical and financial strengths. The middle and upper reaches, simultaneously, are impeded by resource endowment and infrastructure conditions, and their green development falls short. In light of this, assessing the GDCCL in the YREB and examining its spatial disparities and progressive transformation possess both academic merit and utilitarian relevance for fostering regionally harmonized emission reduction and reaching China's "dual-carbon" goals.

2 LITERATURE REVIEW

2.1 Research on the GDCCL

Examination on supply chain effectiveness assessment has largely adopted techniques including stochastic frontier analysis, data envelopment analysis (DEA), and analytic hierarchy process [9-11]. However, existing research is mostly concentrated in the field of traditional logistics, with fewer studies specifically considering cold chain logistics [12]. Being a pivotal metric for appraising regional sustainable development, green development efficiency must incorporate the coordinated interplay between economic output, environmental impact, and resource utilization efficiency [13]. However, most studies fail to fully consider key factors such as environmental constraints and energy consumption in the process of efficiency evaluation, especially the treatment of nondesired outputs. Existing studies have used diverse indicator systems and research methods. Regarding indicator systems, Fang Xin et al. established an evaluation system comprising 14 indicators in three dimensions—socio-economic backdrop, cold chain supply and demand level, and cold chain infrastructure—to measure cold chain development in the YREB [14]. Wang Xiao et al. constructed a cold chain logistics efficiency evaluation framework in two dimensions: infrastructure and technology investment [15]. Methodologically, researchers have used various econometric models. Deng Mengjie et al. integrated the super-efficiency slack-based measure (SBM) alongside the global Malmquist–Luenberger (GML) index to address the challenge of effectiveness assessment within unanticipated output conditions [16]. Li Yihua et al. applied a DEA-BCC model and the Dagum Gini coefficient to the multi-dimensional appraisal of spatial-temporal progression [17]. Qin Xiaohui et al. applied a three-step DEA model to mitigate the disturbance of ecological factors and enhance the precision of effectiveness assessment [18]. Yuan Yakun et al. applied σ convergence and β convergence models to demonstrate the progression of disparities in regional efficiency [19]. Regarding the scope of study, current findings have featured multilevel spatial analyses. Zhang Lu, for instance, analyzed the spatial efficiency differentiation of cold chain logistics in 31 provinces [20]. Focusing on coastal provinces, Li Yajie et al. used a DEA-Malmquist index to reveal dynamic changes in regional efficiency [21]. Barilla et al. measured Italy's total-factor logistics productivity at the national level [22]. Chen Jiming et al. investigated dairy cold chain logistics in North China and analyzed the dynamics shaping technical efficiency [23]. Zhang et al. applied a super-efficiency DEA model to evaluate the logistics effectiveness [24].

Although these studies have important practical and theoretical implications for cold chain logistics development, the following limitations remain: (1) Most studies remain at the level of static efficiency analysis and lack in-depth discussions of the dynamic evolution of total-factor productivity. (2) There is insufficient quantitative analysis of the formation mechanism of spatial heterogeneity in studies of regional differences. (3) Classic DEA approaches struggle addressing unforeseen output and slack variables, that could result in efficiency assessment distortion. The present study, therefore, constructs an evaluation system that includes labor, capital and energy inputs, and dual economic–environmental output dimensions. This additionally leverages super-efficiency SBM and the GML index to statically assess and dynamically dissect the eco-friendly progress effectiveness of cold chain logistics within the YREB from 2013 to 2023. Ultimately, the Dagum Gini coefficient is applied to investigate the origin of geographical disparities. By this approach, the research seeks to offer an innovative scholarly viewpoint and analytical guide regarding the eco-friendly advancement of cold chain logistics.

2.2 Indicator Selection and Data Sources

Informed by previous research, this study analyzes the input and output characteristics of cold chain logistics. In terms of input factors, traditional models usually cover capital input, labor input, and technical level. However, given that cold chain logistics involves technical factors that are difficult to quantify—such as special transportation tools and refrigeration technology—this study does not include technical input for the time being. Additionally, the GDCCL relies significantly on power; therefore, the research incorporates energy consumption in the input indicator system. To conclude, the research's ultimate input indicators comprise labor, capital, and energy; The result metrics are grouped into anticipated outcomes (economic value) and undesired output (environmental costs including carbon emissions).

Existing statistical data do not separately account for the logistics industry. Consequently, drawing upon standard academic methods, this research chooses numerical data from the transportation, warehousing, and postal industries as a proxy for logistics industry data. Given that this study's research object is the GDCCL, to uphold data precision, all input–output variables are scaled through the proportion of the aggregate volume of cold chain logistics pertaining to the cumulative volume of logistical networks within China during that year to assess real input and output in cold chain logistics operations.

Table 1 shows the evaluation system constructed for this study. The basic data come from the China Logistics Development Report. Among them, CO2 emission statistics are calculated based on the carbon emission data for various regions released by the China Carbon Accounting Database.

Table 1 Evaluation Index System for the Efficiency of GDCCL in the YREB

Category	Variable Name	Unit
Input indicators	Fixed-asset investment in cold chain logistics industry	100 million yuan
	Number of people employed in cold chain logistics industry	10,000 people
	Total energy consumption	10,000 tons
Expected output indicators	Cold chain logistics cargo turnover	10,000 tons/km
	Added value of cold chain logistics industry	100 million yuan
Unexpected output	CO2 emissions	10,000 tons

3 METHODS

3.1 Super-Efficiency SBM

Traditional three-stage DEA has limitations in terms of efficiency evaluation, primarily evident in the issue of nonzero slack variables, which leads to overstatements of the efficiency measure of decision-making units. To overcome this, this study introduces the directional distance function of SBM, which can solve the problem of ignoring slack variables. Statically assessing the GDCCL necessitates concurrently analyzing the connection between production inputs and expected outputs, as well as between production inputs and unexpected outputs. This study therefore selects super-efficiency SBM for empirical analysis. This model can not only accurately evaluate the efficiency performance of expected and unexpected outputs relative to input factors but can also overcome the limitations of traditional DEA in terms of comparing efficiency values. By this method, it is capable of delivering a higher precision assessment of the GDCCL. Refer to Formula (1) for comprehensive specifics:

$$\rho=min\left\{\frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{S_i^x}{x_{i0}}}{1-\frac{1}{S_1+S_2}\left(\sum_{k=1}^{s1}\frac{S_k^y}{y_{k0}}+\sum_{l=1}^{s2}\frac{S_l^z}{z_{l0}}\right)}\right\}$$

$$s.t.\begin{cases}\sum_{j=1,j\neq 0}^{n}x_j\beta_j-S_i^r\leq x_{i0};\ \sum_{j=1,j\neq k}^{n}y_j\beta_j+S_k^y\geq y_{k0};\ \sum_{j=1,j\neq k}^{n}z_j\beta_j-S_l^z\leq z_{l0};\forall i,k,l;\\ 1-\frac{1}{S_1+S_2}\left(\sum_{k=1}^{s1}\frac{S_k^y}{y_{k0}}+\sum_{l=1}^{s2}\frac{S_l^z}{z_{l0}}\right)>0;\\ S_i^r\geq 0,S_k^y\geq 0,S_l^z\geq 0,\beta_j\geq 0\forall i,j,k,l;\end{cases} \quad (1)$$

In which xi represents the input index, yk represents the expected output index, zl represents the nonexpected output index, and ρ represents the efficiency value of the GDCCL. When ρ is no less than 1, the GDCCL has attained the effective production frontier; when ρ is less than 1, it has not yet attained. The higher the ρ value, the more favorable the GDCCL in the YREB.

3.2 The Global Malmquist-Luenberge Index Model

Super-efficiency SBM solely has the capacity to assess the fixed efficacy of the decision-making unit within the identical time period. Consequently, to additionally measure the variation in the total-factor productivity of the green development efficiency of cold chain logistics between time period t and time period t+1, this research employs the Global Malmquist-Luenberge (GML) index to investigate the variable efficacy of different decision-making units across distinct temporal intervals. It also evaluates the total-factor productivity including nonexpected output, as follows:

$$\begin{aligned}GML_C^G(x^t,y^t,z^t,x^{t+1},y^{t+1},z^{t+1})&=\frac{E_C^G(x^{t+1},y^{t+1},z^{t+1})}{E_C^G(x^t,y^t,z^t)}\\&=\frac{E_C^{t+1}(x^{t+1},y^{t+1},z^{t+1})}{E_C^t(x^t,y^t,z^t)}\times\left\{\frac{E_C^G(x^{t+1},y^{t+1},z^{t+1})}{E_C^{t+1}(x^{t+1},y^{t+1},z^{t+1})}\times\frac{E_C^t(x^t,y^t,z^t)}{E_C^G(x^t,y^t,z^t)}\right\}\\&=\frac{E_C^{t+1}(x^{t+1},y^{t+1},z^{t+1})}{E_C^t(x^t,y^t,z^t)}\times\frac{TG_C^{G,t+1}(x^{t+1},y^{t+1},z^{t+1})}{TG_C^{G,t}(x^t,y^t,z^t)}\\&=(GML)EC_C\times(GML)TC_C\end{aligned} \quad (2)$$

When GML > 1, the total-factor productivity of the GDCCL throughout this time frame rises; when GML < 1, it falls; when GML = 1, it stays constant. Given that the constant returns to scale, the Global Malmquist-Luenberge may be split into technical efficiency change (EC) and technical progress change (TC).

3.3 Dagum Gini Coefficient

To additionally investigate spatial variations in the green development of cold chain logistics in the YREB, this study employs the Dagum Gini coefficient to assess the extent of geographical disparities. In accordance with the coefficient decomposition method and the conceptual basis of the Gini coefficient, the formulas are outlined below:

$$G=\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_n}\frac{\left|y_{ji}-y_{hr}\right|}{2n^2\mu} \tag{3}$$

$$G_{jj}=\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\frac{\left|y_{ji}-y_{hr}\right|}{2n^2\mu} \tag{4}$$

$$G_{jh}=\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\frac{\left|y_{ji}-y_{hr}\right|}{n_j n_h(\mu_j+\mu_h)} \tag{5}$$

Within Equation (3), k denotes the aggregate count of zones. Given the YREB is segmented into upper, middle, and lower reaches, k equals 3. n signifies the count of provinces, with an aggregate of 11 provincial and municipal entities. nj (nh) represents the quantity of provinces in zone j (h), yji (yhr) indicates the green development efficiency metric of province i (r) in zone j (h), and μ reflects the mean green development effectiveness across the 11 provincial and municipal entities. The Dagum Gini coefficient breaks down the total Gini coefficient G into the listed three components: (I) share of intraregional differences (Gw), (II) share of interregional differences (Gnb), and (III) share of hypervariable density (Gt). The formulas are as follows.

$$G=G_w+G_{nb}+G_t \tag{6}$$

$$G_w=\sum_{j=1}^{k}G_{jj}P_jS_j \tag{7}$$

$$G_{nb}=\sum_{j=2}^{k}\sum_{h=1}^{j-1}G_{jh}(P_jS_h+P_hS_j)D_{jh} \tag{8}$$

$$G_t=\sum_{j=2}^{k}\sum_{h=1}^{j-1}(1-D_{jh})G_{jh}(P_jS_h+P_hS_j)D_{jh} \tag{9}$$

$$D_{jh}=\frac{d_{jh}-p_{jh}}{d_{jh}+p_{jh}} \tag{10}$$

$$P_j=\frac{n_j}{n} \tag{11}$$

$$S_j=\frac{n_j\mu_j}{n_\mu} \tag{12}$$

In Equations (6)–(12), Djh denotes the proportional influence of the expansion of the efficiency measure of green development across zones j and h; and djh reflects the disparity in the expansion of the efficiency measure of green development across zones j and h. This segmentation approach uncovers the origin mechanism and core attributes of geographical disparities in the GDCCL across 11 regional and municipal entities in the YREB.

4 RESULTS AND ANALYSIS

4.1 Static Analysis of Green Efficiency Development in the YREB

This study employs Dearun software to measure the efficiency of GDCCL in 11 provincial and municipal units in the YREB between 2013 and 2023. Super-efficiency SBM is adopted, and the model is set as nonguided and constant returns to scale (CRS). Table 2 shows the results.

Table 2 Static Efficiency Values of the GDCCL in the YREB, 2013–2023

Region	Year											Mean
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	
Shanghai	0.423	0.565	0.465	0.424	0.515	0.609	0.659	1.047	1.011	1.004	1.078	0.709
Jiangsu	1.005	0.593	0.508	0.488	0.550	0.539	0.522	0.597	1.017	1.002	1.016	0.712
Zhejiang	0.467	0.524	0.514	0.542	0.559	0.597	0.601	0.553	0.601	0.691	0.782	0.585

Region	Year											Mean
Anhui	0.604	0.601	0.470	0.473	0.472	1.019	0.954	0.948	1.034	0.958	1.051	0.780
Jiangxi	0.473	0.451	0.404	0.435	0.515	0.611	0.490	0.496	0.620	0.718	0.754	0.542
Hubei	0.281	0.298	0.300	0.271	0.292	0.408	0.400	0.344	0.448	0.527	0.627	0.381
Hunan	0.364	0.357	0.305	0.321	0.364	0.393	0.220	0.226	0.258	0.273	0.360	0.313
Chongqing	0.216	0.259	0.239	0.253	0.273	0.342	0.339	0.343	0.398	0.441	0.469	0.325
Sichuan	0.216	0.195	0.218	0.173	0.185	0.190	0.182	0.192	0.203	0.210	0.249	0.201
Guizhou	0.298	0.323	0.303	0.309	0.358	0.266	0.180	0.184	0.221	0.236	0.270	0.268
Yunnan	0.113	0.108	0.113	0.115	0.124	0.213	0.179	0.185	0.230	0.263	0.282	0.175
Downstream area	0.625	0.571	0.489	0.482	0.524	0.691	0.684	0.786	0.916	0.914	0.982	0.697
Midstream area	0.373	0.369	0.337	0.342	0.390	0.470	0.370	0.355	0.442	0.506	0.580	0.412
Upstream area	0.211	0.221	0.218	0.213	0.235	0.253	0.220	0.226	0.263	0.288	0.317	0.242
Entirety	0.406	0.389	0.349	0.346	0.382	0.471	0.430	0.465	0.549	0.575	0.631	0.454

During 2013 through 2023, the mean total efficiency measure of the YREB exhibited a wavering ascending pattern (Figure 1). Its average value increased from 0.406 in 2013 to 0.631 in 2023, an increase of 55.49%. During this period, the efficiency value decreased slightly from 0.389 to 0.346 from 2014 to 2016. However, it rebounded after 2017, and the growth rate accelerated from 2019 to 2023, with an average annual growth rate of 10.07%.

Regarding geographical disparities, the efficiency of the green development of cold chain logistics demonstrates prominent spatial layout features. Regions in the middle and lower reaches of the YREB exhibit superior operational performance, while these areas present a wavering ascending advancement trajectory. Indeed, the green development efficiency of the lower reaches of the YREB stands at the peak, attaining 0.697. Nevertheless, within the period 2014–2016, the efficiency of the region exhibited a declining trajectory, and the intra-regional disparities were notably pronounced. The mean green development efficiency of the middle reaches of the YREB is 0.412, which is comparatively less than that of the lower reaches, yet the general advancement trajectory is favorable. The upper reaches possess the minimal efficiency at merely 0.242. Despite the overall green development efficiency of the lower reaches being somewhat sluggish, its growth capacity is substantial, and it is anticipated to strengthen its leading role in the green development of cold chain logistics in the future.

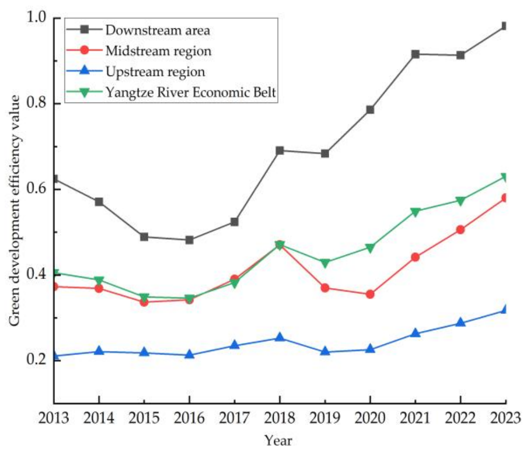

Figure 1 Green Development Level of Cold Chain Logistics in the YREB: Static Development Level Change Chart

In terms of differences in efficiency values at the provincial level, Shanghai shows particularly strong performance. After 2020, its efficiency value exceeded 1.0 and reached 1.078 in 2023, significantly ahead of other provinces, demonstrating its advantages as a regional economic center. The efficiency value trends of Jiangsu and Zhejiang are relatively similar, but Jiangsu's growth rate during 2020–2021 is significantly faster than that of Zhejiang. As an important province in the downstream area, Anhui's efficiency value jumped to 1.019 in 2018 and has maintained a high operating trend since then. Hubei's performance is relatively outstanding, with an efficiency value of 0.627 in 2023, an increase of 122.7% compared with 2013. The efficiency values of Hunan is generally low, with average values of 0.313, respectively, but Jiangxi significantly improved in 2023, having an efficiency value of 0.754. Chongqing's and Sichuan's efficiency values maintain a fairly steady pattern, reaching 0.469 and 0.249, respectively, in 2023. Yunnan's growth rate is the most impressive; its efficiency value in 2023 increased by 149.7% compared with that in 2013, showing a strong development trend.

4.2 Dynamic Analysis of Green Development Levels in the YREB

Additionally, to investigate evolving dynamics in the green development efficiency of cold chain logistics within the YREB, the research employs Dearun to measure the total-factor productivity of the input–output metrics of 11 provincial and municipal entities within the YREB between 2013 and 2023 according to the GML index. GML is applied to concurrently assess and dissect the GDCCL. Tables 3 and 4 present the findings. To clearly illustrate the evolving features of efficiency progression, Figure 2 depicts the evolving pattern of the GML index for total-factor productivity and its segmentation metric for each provincial and municipal entity.

Table 3 The Global Malmquist-Luenberge (GML) Value of Cold Chain Logistics in the YREB, 2013–2023

Region	Year									
	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	2018–2019	2019–2020	2020–2021	2021–2022	2022–2023
Shanghai	1.3352	0.8220	0.9119	1.2162	1.1809	1.0819	1.5897	0.9653	0.9931	1.0740
Jiangsu	0.5902	0.8573	0.9594	1.1268	0.9814	0.9680	1.1426	1.7043	0.9858	1.0138
Zhejiang	1.1222	0.9813	1.0553	1.0312	1.0670	1.0071	0.9205	1.0867	1.1487	1.1320
Anhui	0.9953	0.7816	1.0070	0.9968	2.1601	0.9360	0.9944	1.0909	0.9260	1.0972
Jiangxi	0.9522	0.8964	1.0764	1.1841	1.1852	0.8029	1.0128	1.2483	1.1591	1.0490
Hubei	1.0585	1.0086	0.9032	1.0775	1.3946	0.9803	0.8593	1.3041	1.1752	1.2185
Hunan	0.9821	0.8544	1.0504	1.1334	1.0811	0.5598	1.0270	1.1407	1.0574	1.3201
Chongqing	1.1962	0.9230	1.0601	1.0765	1.2554	0.9912	1.0113	1.1592	1.1086	1.0636
Sichuan	0.8998	1.1197	0.7959	1.0681	1.0234	0.9612	1.0541	1.0560	1.0379	1.1825
Guizhou	1.0863	0.9363	1.0224	1.1569	0.7429	0.6779	1.0181	1.2032	1.0686	1.1447
Yunnan	0.9602	1.0446	1.0204	1.0750	1.7186	0.8414	1.0305	1.2423	1.1441	1.1901
Mean	1.0162	0.9296	0.9875	1.1039	1.2537	0.8916	1.0600	1.2001	1.0731	1.1350

As illustrated in Table 3, the total-factor productivity (GML index) of cold chain logistics across YREB provinces exhibits pronounced wavering. During 2014 through 2016 and 2018 through 2019, the mean GML index for total-factor productivity of cold chain logistics in the YREB remained sub-1, indicating a downward trend during this period; in other years, it was higher than 1, indicating an overall growth trend. During 2017–2018, it reached 1.2537, the highest value in the study period.

At the province level, Shanghai had the lowest GML index value during 2014–2015, which was only 0.8220, but it then increased year by year, reaching 1.5897 during 2019–2020, reaching a peak, and then gradually slowing down. The GML index values of Jiangsu and Zhejiang reached a peak of 1.7043 and 1.1487, respectively, during 2020–2021 and 2021-2022, and although there were fluctuations afterward, they generally remained at a high level. The GML value in Anhui showed a gradual increase and then a slow decline, peaking at 2.1601 during 2017-2018. Jiangxi peaked at 1.2483 in 2020-2021 and finally reached 1.1591 and 1.0490 in 2022-2023, respectively. The GML index values in Hubei and Hunan showed a deep "V" shape throughout the study period, reaching 1.2185 and 1.3201 respectively from 2022 to 2023. The GML index values of Chongqing, Sichuan, Guizhou and Yunnan were 1.1962, 0.8998, 1.0863 and 0.9602 respectively from 2013 to 2014, and then showed a fluctuating upward trend, reaching 1.0636, 1.1825, 1.1447 and 1.1901 respectively from 2022 to 2023. From the overall trend, the average GML index of the total-factor productivity of cold chain logistics in the YREB has increased year by year, from 1.0162 during 2013–2014 to 1.1350 during 2022–2023, indicating a positive overall development trend.

To further explore the evolving eco-friendly progress of cold chain logistics across YREB provinces, this research breaks down and examines the GML index of each province. Table 4 and Figure 2 illustrate the findings. The GML index of total-factor productivity for cold chain logistics in the YREB demonstrates a gradual ascending trajectory overall, with intermittent variations. Between 2017–2018, the surge in the GML index was most pronounced, primarily driven by the swift expansion of the technological progress index. This indicates that during this phase, technical and technological standards and eco-friendly progress levels of cold chain logistics were undergoing consistent advancement. However, phase discrepancies existed in the coordination between TC and EC.

Table 4 Mean GML Index and Decomposition Results for Cold Chain Logistics in the Provinces and Cities in the YREB

Region	EC	TC	GML
Shanghai	1.0503	1.0639	1.1170
Jiangsu	1.0206	1.0596	1.0329
Zhejiang	1.0224	1.0696	1.0552
Anhui	0.9958	1.0895	1.0985
Jiangxi	1.0448	1.0411	1.0566
Hubei	1.0579	1.0354	1.0980
Hunan	0.9767	1.0644	1.0206
Chongqing	1.0359	1.0690	1.0845
Sichuan	0.9866	1.0625	1.0199
Guizhou	0.9252	1.1931	1.0057
Yunnan	1.0816	1.0601	1.1267

Further examination suggests that the increase of the total-factor productivity of cold chain logistics in seven provinces and cities (Shanghai, Jiangsu Province, Zhejiang Province Anhui Province, Hunan Province, Chongqing, Sichuan Province, and Guizhou Province) heavily relies on the TC index. The growth of the total-factor productivity of cold chain logistics in Hubei Province, and Yunnan Province relies more on rises in the EC value. As illustrated in Figure 2, the pattern of variation in the total-factor productivity index of cold chain logistics in the YREB is closely aligned with that of the TC index, highlighting reliance on the catalyst role of technological innovation.

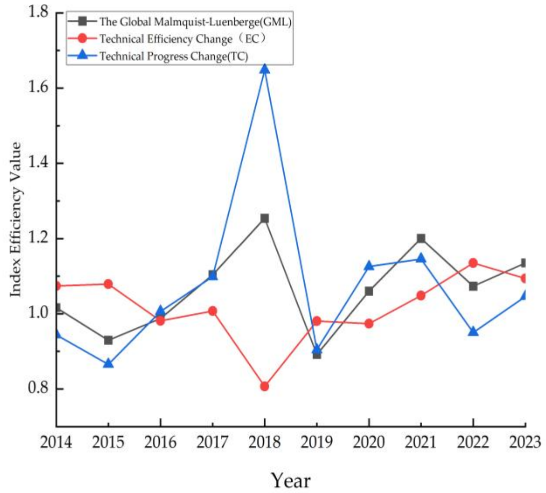

Figure 2 Changing Trends of the GML Index and Its Decomposition Index of Cold Chain Logistics in the YREB

4.3 Regional Differences in the Level of GDCCL in the YREB

4.3.1 Overall difference

The Dagum Gini coefficient and its decomposition approach is applied to investigate geographical disparities in the GDCCL within the YREB. Figure 3 displays the outcomes. As apparent from the visualization, the aggregate divergence in the level of GDCCL across the YREB is substantial. The Gini coefficient spans from 0.2031 to 0.3339, exhibiting a wavering ascending pattern overall. Specifically, the aggregate Gini coefficient for the YREB progressively declined from 0.2967 in 2013 to 0.2031 in 2015 and subsequently demonstrated a wavering upward trajectory, attaining a zenith of 0.3339 in 2020 before marginally reducing. This signifies that the general green development disparity in the YREB contracted between 2013 and 2015 yet progressively widened post-2015, notably following 2017, with the divergence escalating notably.

4.3.2 Intra-regional differences

As illustrated in Figure 3, the Gini coefficients of the green development of cold chain logistics in the proximal, central, and distal segments of the YREB demonstrate marked spatial differences and stage characteristics. Generally, the Gini coefficient of the upper reaches persisted at elevated levels over an extended duration. The regional average ranking is articulated as: upper reaches > middle reaches > lower reaches, signifying that the internal imbalance in the upper reaches is the most pronounced. The downstream areas show a W-shaped fluctuation: it was 0.1883 in 2013, and it dropped to the lowest point of 0.0238 in 2015, and then, it experienced a small rebound, fall, and rise again. The fluctuation rebounded to 0.0588 in 2023, and the overall imbalance converged compared with that in 2013. The middle reaches showed a single-valley trend of “first decline and then rise”: it was 0.1144 in 2013, fell to the valley value of 0.0685 in 2015, and then continued to rise, reaching 0.1508 in 2023, with a cumulative increase of 31.8%. This indicates that the trend of imbalance in the region’s green development has significantly expanded since 2018. The upstream region showed a trend of “slow decline–fluctuation–recovery”: it was 0.1646 in 2013, fell to the lowest point of 0.1265 in 2018, and then fluctuated slightly upward to 0.1323 in 2023. The overall fluctuation narrowed, and the imbalance tended to be relatively stable.

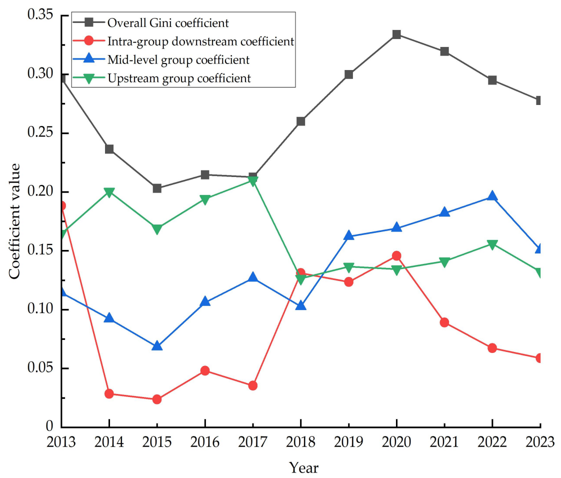

Figure 3 Differences in Green Development Levels in the YREB as a Whole and in Each Region

Generally, though the GDCCL is unbalanced in the upstream region, it has shown a trend toward convergence in recent years. Regional differences in the midstream region have expanded sharply since 2018, and the trend toward imbalance has intensified. The downstream region saw a rapid rise in imbalances in 2017 and slowly adjusted back in the past five years.

4.3.3 Regional differences

The change trend of the interregional Dagum Gini coefficient (Gb) of the GDCCL in the YREB in Figure 4 indicates that the differences between the downstream-middle and downstream-upstream regions have shown a significant upward trend. This indicates that imbalances in the level of GDCCL between regions are intensifying, and the Gini coefficient between the midstream and upstream regions has declined. Specifically, the Gini coefficient of the downstream-middle reaches has increased from the initial 0.2619 to 0.3775, which is the most significant increase, and then slowly decreased to 0.2571. This indicates that the sustainable growth disparity among the two areas continues to widen and eases in 2023, which may be attributable to the further strengthening of the downstream region's advantages in green technology, policy support, and capital investment, while the midstream region has failed to follow up synchronously. The Gini coefficient of the downstream-upstream increased from 0.4955 to 0.5113. Although this increase is slightly lower than that of the downstream-middle group, it still reflects a clear differentiation trend. This indicates that the upstream region lags relatively behind in the green transformation of cold chain logistics, and the technological generation gap and resource endowment differences with the downstream region may be further solidified. The Gini coefficient of the middle-upstream region increased from 0.2825 to 0.3129, showing the most stable change gap. This indicates that although the middle-stream region has certain transitional advantages, it has not been able to bridge the gap with the upstream region and may even see an intensification of gradient differentiation owing to resource competition.

In terms of the change stage, the downstream-upstream and downstream-middle stream groups show a clear upward trend from 2017 to 2020. The upward trend of the middle-upstream region is relatively gentle from 2015 to 2018 and then declines, reaching a low point in 2020 and then rising again. This could be related to factors such as the uneven implementation of regional development policies within the YREB, the obstructed diffusion of green technology, or the rise of local protectionism. It is worth noting that the Gini coefficient of the downstream-upstream region is always higher than that of the downstream-middle stream and middle-upstream regions. This indicates that the polarization effect of the downstream region is significant, and its leading position in green development has further widened the gap with the middle and upstream regions. This phenomenon suggests that if there is a lack of an effective regional coordination mechanism, advantaged regions will continue to gather resources, while underdeveloped regions will fall into a low-level lock. Future policies need to focus on technology transfer, balanced infrastructure layout, and cross-regional ecological compensation mechanisms to curb the widening trend of regional disparities and promote the GDCCL throughout the region.

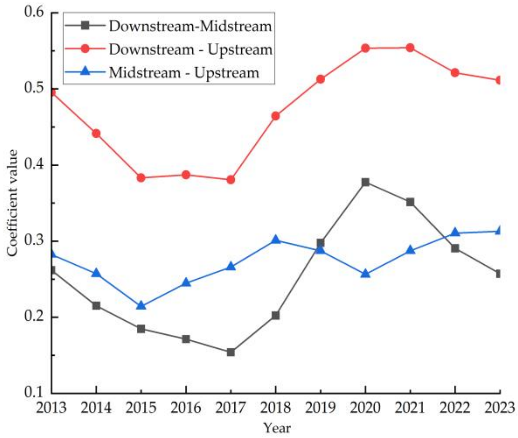

Figure 4 Regional Gaps in the GDCCL in the YREB

5 CONCLUSIONS AND IMPLICATIONS

5.1 Conclusions

This research regards 11 provincial and municipal units in the YREB as the focal point, establishes an assessment index framework for the GDCCL, employs a nonexpected super-efficiency SBM model to compute static efficiency, and applies the GML index to determine the total-factor productivity of 11 provincial and municipal entities in the YREB. Additionally, the Dagum Gini coefficient is utilized to expose geographical disparities and their origins. The outcomes follow:

Initially, throughout the research period, the aggregate green static efficiency of cold chain logistics in the YREB remains comparatively low, averaging merely 0.4538. Downstream to upstream presents a hierarchical spatial pattern. All regions stray from the production frontier. The comparative deficiency in technological investment constitutes the primary limitation, but the total-factor productivity of the GDCCL is in an ascending phase.

Secondly, the segmentation of the GML index demonstrates that technical efficiency and technological progress collectively enhance the total-factor productivity, but technological progress is preeminent. When the level of GDCCL is suboptimal, it is required to enhance technical efficiency to attain expansion in total-factor productivity. When the level of GDCCL is elevated, it is required to attain expansion in total-factor productivity through technological progress. Ultimately, there are marked regional disparities. The Gini coefficient for the GDCCL spans from 0.2031 to 0.3339 and typically exhibits a pattern of "first declining and then ascending." Across regions, the midstream areas display a wavering ascending trajectory, whereas the downstream and upstream areas display a wavering descending trajectory. The share of regional disparities prevails over the aggregate differences.

5.2 Implications

This research holds both theoretical merit and applied significance for assessing the eco-friendly advancement level of cold chain logistics within the YREB and examining geographical disparities. This investigation revealed that the eco-friendly advancement efficiency of cold chain logistics across the YREB demonstrates a tiered spatial pattern of "downstream > midstream > upstream," with significant regional differences and a fluctuating and expanding trend. Hence, in the process of promoting green transformation, both efficiency improvement and regional equity must be taken into account. The segmentation outcomes of the GML index indicate that the share of technological progress for the advancement of total-factor productivity surpasses the share of technical efficiency. This points to a pathway for the progress of the sector: green technology innovation should be regarded as the primary catalyst, and critical technologies including low-carbon refrigeration and smart logistics should be integrated. Additionally, an efficient technology-diffusion mechanism must be implemented to facilitate the gradient transfer of cutting-edge technologies from downstream zones to midstream and upstream zones. This investigation also identified marked disparities in the growth limitations of various regions. Therefore, policies must be tailored to regional specifics: downstream zones should concentrate on refining the energy configuration and enhancing the intelligence standard. Midstream areas need to strengthen the standardized construction and operation management of cold chain infrastructure. Upstream areas can combine their ecological advantages to explore special development paths such as new-energy refrigerated vehicles and green warehousing. In addition, the current cold chain logistics industry has problems such as incomplete statistical data and an imperfect evaluation system. Going forward, it becomes essential to formulate a higher precision industry database, enhance key indicators including instances of greenhouse gas emission density and the ratio distribution of renewable energy, and supply a more robust foundation for policy development. This study both offers empirical validation for the green transformation of cold chain logistics in the YREB and additionally uncovers a trajectory toward establishing a coordinated regional development mechanism. Future research can further combine multidimensional factors such as the policy environment and market demand to explore the mechanisms of difference formation and help the industry achieve higher quality sustainable development.

5.3 Limitations

First, in the construction of the indicator system, this study does not fully consider the technical input factors of cold chain logistics (e.g., refrigeration technology, information level) and only uses labor, capital, and energy as input indicators, which may lead to deviations in efficiency evaluation. Second, there are limitations at the data level. Owing to the incomplete statistical data for the cold chain logistics industry, this study uses transportation, warehousing, and postal industry data as substitutes and estimates cold chain logistics data through proportional conversion. This method might not accurately reflect the actual situation. Additionally, though this study employs super-efficiency SBM and the GML index, the examination of elements that affect efficiency (for instance, policy backing, marketization level) is inadequate, and there is a deficiency of thorough examination of the driving forces. Finally, although the regional difference analysis reveals spatial differentiation, it does not further explore the specific reasons for the formation of differences (e.g., industrial structure, infrastructure), and the pertinence of the policy recommendations needs to be strengthened. Future research can combine qualitative analysis methods, supplement technical input indicators, and use more accurate data sources to improve the scientific nature of the conclusions and the practical guidance value.

COMPETING INTERESTS

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