



Assessing economic sustainability and ecological efficiency with genuine progress indicator: a case study of the Yangtze River Delta from 2000 to 2018

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Abstract

To achieve urban sustainability, it is critical to enhance the environment, economy, and society simultaneously. This study adopted the revised genuine progress indicator (GPI) and ecological footprint (EF) to evaluate the ecological efficiency and economic sustainability of the Yangtze River Delta from 2000 to 2018. Spatial analysis was utilized to identify spatial autocorrelation. A total of 27 cities were then partitioned through *k*-means cluster analysis. The results showed that GPI and ecological efficiency improved rapidly, but economic sustainability showed a downward trend. GPI and GDP had a high degree of spatial correlation, especially in Suzhou-Wuxi-Changzhou Metropolitan Area. However, no spatial correlation existed between GPI and EF. The city with high GEE can reach 3000 \$/gha, indicating the city consumed 1 global hectare to create \$3000 of genuine economic growth. Shanghai, Hangzhou, and Taizhou were cities with the highest level of economic sustainability and ecological efficiency. The spatiotemporal characteristics of economic sustainability and ecological efficiency revealed in this study will provide theoretical guidance for alleviating ecological pressure and promoting economic sustainable development.

Keywords Genuine progress indicator · Ecological footprint · Ecological efficiency · Economic sustainability · Yangtze River Delta

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Introduction

Since the implementation of the reform and opening-up policy in 1978, China has experienced tremendous economic growth. China's urban population exceeded the rural population for the first time in 2011, and the urbanization rate was over 60% in 2019 (National Bureau of Statistics 2020). Rapid urbanization has significantly affected the natural environment and human life, resulting in a series of environmental problems such as air pollution, water pollution, energy and resource constraints, and societal issues such as income inequity (Bloom et al. 2008; Grimm et al. 2008). Urban sustainability, balancing environment, economy, and society at multiple scales, is a path and an ultimate goal to achieve urban development (Wu. 2010). Among the three pillars of urban sustainability above, environmental protection and economic growth usually contradict each other as reducing resource consumption probably slows down economic development. Hence, improving economic sustainability and ecological efficiency is critical to maximize economic benefits and minimize ecological pressure (Jin et al. 2020).

Economic sustainability is the ability to allow people to prosper and make economic progress under ecological balance and long-term social development (Santos and Martins. 2007; Long and Ji. 2019). Studies on economic sustainability cover energy, ecological-economic system, technological innovation, manufacturing, and other aspects, mainly using socio-economic data (e.g., GDP, public finance income) (Martínez-Bravo et al. 2019; Khan et al. 2021; Maama et al. 2021). GPI, a substitute of GDP that uses monetary valuation to track and aggregate trends across the economy, environment, and society, has been widely used to assess economic sustainability (Bagstad et al. 2014; Brown and Lazarus 2018; Kenny et al. 2019; Fox and Erickson 2020). GPI is the revised version of the index of sustainable economic welfare (Lawn and Clarke 2010). Lawn (2003) provided a basis for theoretical support and believed that GPI was a proper indicator for assessing income and welfare because it was consistent with Fisher's income and capital concepts. GPI not only considers market welfare and basic capital services but also involves various environmental and social costs and covers extensive sustainable development goals. It generally includes more than 20 individual indicators. As the availability of GPI data has increased, the index has gained wider acceptance as a relatively feasible approximation of economic welfare (Lawn 2003; Wen et al. 2007; Kubiszewski et al. 2013; Long and Ji 2019). The comparison of GPI and GDP aids in evaluating the economic growth quality and offers valuable information for economic sustainability (Huang et al. 2016). Hashim et al. (2019) assessed the progress of South Korea and Malaysia through

GPI and GDP to study the impact of International Monetary Fund debt and capital control on sustainable development. Andrade and Garcia (2015) found that the gap between GPI and the GDP of Brazil increased from 1970 to 2010, implying the country was facing unsustainable concerns. Long and Ji (2019) showed that the gap between GPI and GDP widened, indicating that the increase in welfare lagged behind the growth of the economic scale.

Ecological efficiency refers to the creation of more goods and services using fewer resources to reduce waste and pollution (Glavič et al. 2012), which reflects the performance of sustainable development in economic, resource, environmental, and social aspects (Freeman et al. 1973; Mickwitz et al. 2006). The methods for ecological efficiency assessment mainly include ratio approach (Yu et al. 2013; Yang and Yang 2019; Jin et al. 2020), life cycle assessment (Michelsen et al. 2006; García et al. 2018), material flow analysis (Daniels and Moore 2001; Wang et al. 2016), energy analysis (Brown and Ulgiati 2004; Geng et al. 2010), and data envelopment analysis (Daniels and Moore 2001; Rebolledo-Leiva et al. 2019). The ratio approach has been widely used because it is comparable in reflecting the actual situation of economic growth and the environmental pressure. In previous studies, GDP is used as a numerator in the ratio method to reflect the expansion of economic strength and economic scale (Kubiszewski et al. 2013; Ezebilo et al. 2015; Jones and Klenow 2016; Brown and Lazarus 2018). The denominator of the ratio refers to the consumption of resources and environmental pollution generated, such as pollution emissions (e.g., CO₂, SO₂), material flow indicators (e.g., direct material input), and EF (Zhang et al. 2008; Yang and Yang 2019). EF quantitatively analyzes the regional resource supply and demand structure and covers the environmental and social dimensions (Rees 1992; Wackernagel et al. 1999; Kongbuamai et al. 2020b). It has been widely used in recent studies (Ahmed et al. 2020; Danish and Khan. 2020; Kongbuamai et al. 2020a) because it focuses on the direct and indirect impacts of production and consumption activities on the environment (Ulucak and Bilgili 2018). Yang and Yang (2019) evaluated the annual ecological efficiency of China from 1978 to 2016 by a modified EF model. Marti and Puertas (2020) analyzed the ecological efficiency of African countries through the Data Envelopment Analysis model based on EF and biocapacity.

The Yangtze River Delta urban agglomeration is one of the regions in China with the highest level of urbanization, the most dynamic economy, and the highest degree of openness (Yu et al. 2020). In 2019, the Central Committee of the Communist Party of China proposed the "outline of the integrated regional development of the Yangtze River Delta," marking that the region has entered a period of accelerated development. With rapid economic growth, is

Yangtze River Delta urban agglomeration economically sustainable? Is it ecologically efficient? What are the urban development directions for agglomeration’s sustainability? To investigate this, the study formulated the ratio of GPI to GDP to reflect economic sustainability, which evaluated whether the economic growth rate and the promotion of social welfare match. Meanwhile, the ratio of GPI to EF was adopted to measure the genuine ecological efficiency of the Yangtze River Delta urban agglomeration. Evaluating the economic sustainability and ecological efficiency of the Yangtze River Delta will provide references for optimizing the spatial distribution of economic activities and resource consumption, and theoretical guidance for alleviating ecological pressure and promoting economic sustainable development.

Materials and methods

Study area

The Yangtze River Delta urban agglomeration covers an area of 358,000 square kilometers and has a population of 163 million, accounting for 11.75% of China’s population (Fig. 1). The Yangtze River Delta urban agglomeration is one of the most densely populated areas on the planet and one of the regions with the highest level of urbanization (Yu et al. 2020). It includes 27 cities, subordinate to three provinces (Zhejiang, Jiangsu, Anhui) and one municipality (Shanghai). Shanghai is China’s largest economic center and is of great importance in China’s economic development, and it has the same administrative level as the three provinces. This study

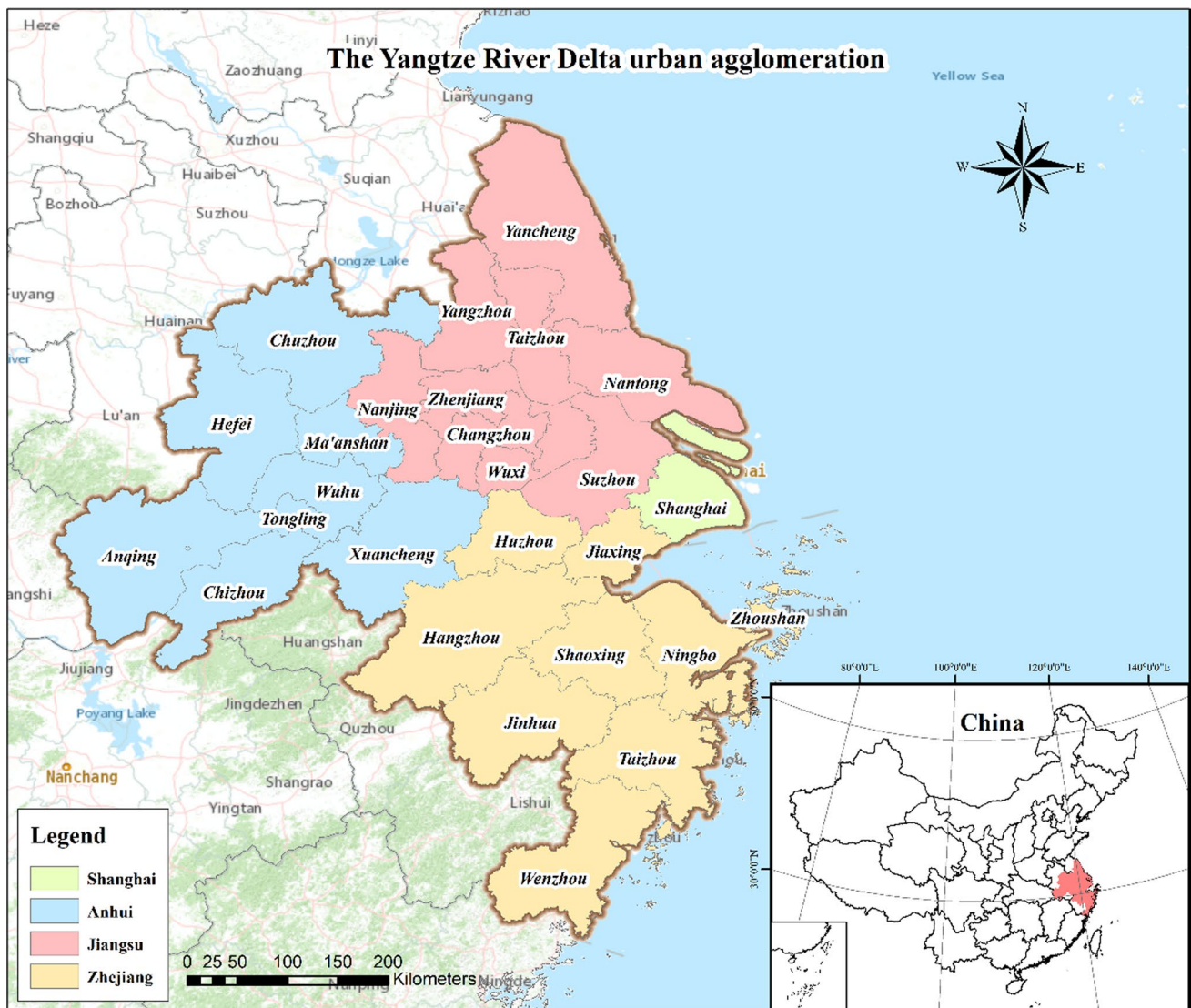


Fig. 1 Location of the study area

made comparisons at the provincial scale and the urban scale. Shanghai was analyzed at the above two scales.

Data source

In this study, the socio-economic data were mainly from the statistical yearbooks of cities, Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, and Anhui Statistical Yearbook from 2000 to 2018. Environmental data were mainly from the statistical yearbook of each city and the China Environmental Statistics Yearbook from 2000 to 2018. The land use data were from the Institute of Geographical Sciences and Natural Resources Research of the Chinese Academy of Sciences, and the statistics were conducted every 5 years (in 2000, 2005, 2010, and 2015). This was consistent with the data sources of other studies on GPI and EF (Wen et al. 2007; Huang et al. 2016; Long and Ji 2019). As most missing values occurred between two interval years, the linear interpolation method was used to fill the data based on the closest available data by SPSS Statistics 25 (Huang et al. 2016; Huang 2018).

Research methods

The study proposed the economic sustainability (ES) composite index (the ratio of GPI to GDP) to assess economic sustainability and the genuine ecological efficiency (GEE) composite index (the ratio of GPI to EF) to evaluate the ecological efficiency of the Yangtze River Delta

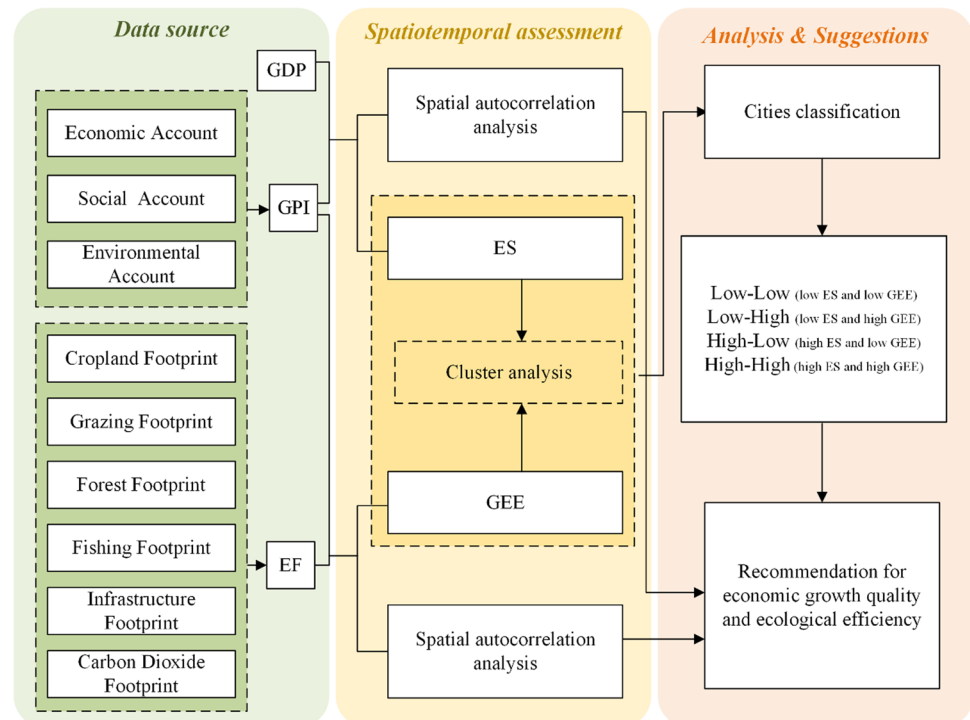
urban agglomeration from 2000 to 2018. The framework was mainly composed of three parts as shown in Fig. 2: (1) depicting the temporal trends of GPI, ES, and GEE; (2) analyzing spatial autocorrelation between GPI and EF, and GPI and GDP based on the bivariate local Moran's I ; (3) rezoning 27 cities based on cluster analysis of GEE and ES.

Genuine progress indicator

GPI consists of three aspects: economic growth quality, environmental sustainability, and social welfare. Each aspect is composed of positive and negative indicators. Positive indicators can bring positive contributions to social welfare, such as personal consumption expenditures, services of consumer durables, and the value of housework and parenting. Negative indicators can reduce GPI and bring losses to social welfare, such as adjustment for unequal income distribution, cost of family breakup, and depletion of nonrenewable resources.

In this study, the indicators were adjusted as follows based on data availability (Wen et al. 2007; Huang et al. 2016): first, due to the dual system of urban and rural areas in China, the income of residents in the statistical yearbook was surveyed separately from urban and rural areas, so the Gini coefficient in the “adjustment of unfair distribution” can only be calculated separately. Second, the main statistics of pollution cost were the government's investment in environmental pollution control. The loss caused by air pollution was not calculated, so air pollution was counted separately. Third, net international debt was removed. This is mainly because international net debt is

Fig. 2 The structure of the research



often used at the national level, but it is negligible in the city’s GPI (Beça and Santos 2010). Some studies also showed that the impact of international net debt on social welfare is not significant (Wen et al. 2007). The description and data source of each indicator in the GPI was presented in Appendix Table 3 . The GPI index system was summarized in Table 1.

Economic sustainability

ES represents the extent of the city’s genuine economic development. GDP is the most common indicator for measuring regional economic growth, and GPI is used to measure the economic growth quality and focus on actual economic development. Therefore, the ratio of GPI to GDP in this study was used to evaluate economic growth sustainability (Hashim et al. 2019; Long and Ji 2019). ES was calculated as follows:

$$ES = GPI/GDP$$

where *ES* is the genuine economic development level of the region. *GPI* is the regional genuine economic development indicator per capita, and *GDP* is the gross domestic product per capita in the region. The higher the ES, the higher the economic sustainability.

Genuine ecological efficiency

GEE is the ratio of *GPI* to *EF*, which reflects the output efficiency of natural efficiency under the level of economic growth

quality. *EF* was introduced into the calculation of *GEE*, which evaluated the utilization efficiency of natural resources in genuine economic growth, and studied the relationship between economic growth quality and environmental consumption (Yue et al. 2016). The calculation of *GEE* was as follows:

$$GEE = GPI/EF_p$$

where *GEE* is the genuine ecological efficiency of the region, *GPI* is the genuine economic growth indicator per capita, and *EF* is the environmental consumption per capita of the region. The greater the value of genuine ecological efficiency, the higher the efficiency of natural resources and the greater the sustainability of regional economic development (Jin et al. 2020).

EF refers to the total area of production land, which mainly includes six account types: cropland, grazing, forest, fishing, infrastructure, and carbon dioxide. Based on the equilibrium factor (Xie et al. 2008; World Resources Institute. 2013), *EF* was calculated according to the accounting framework of the Global Footprint Network (Borucke et al. 2013) as follows:

$$EF_p = \sum_i \frac{P_i}{Y_{w,i}} \cdot EQF_i$$

where *p* is the consumption (or carbon dioxide emitted) of each primary product *i* in the city; *Y_{w,i}* is the average productivity of the global biological resource product *i* (or the

Table 1 GPI in this study

Dimensions	Indicators	Contribution
Economy	Personal consumption expenditures	+
	Adjustment for unequal income distribution (for rural residents)	-
	Adjustment for unequal income distribution (for urban residents)	-
	Cost of consumer durables	-
	Services of consumer durables	+
Society	Cost of crime	-
	Cost of automobile accidents	-
	Cost of commuting	-
	Cost of family breakup	-
	Cost of underemployment	-
	Change of leisure time	+
	Value of housework and parenting	+
	Value of volunteer work	+
Environment	Cost of pollution (air pollution is excluded)	-
	Cost of air pollution	-
	Change of wetlands	-
	Change of farmland	-
	Change of forest	-
	Depletion of nonrenewable resources	-
	Cost of long-term environmental damage	-

*: + indicates a positive impact on GPI; - indicates a negative impact on GPI

average CO₂ absorption capacity of the global woodland and grassland) (Xie et al. 2008); EQF_i is the equilibrium factor for the bio-productive land that provides consumption item i .

Spatial autocorrelation

The global Moran's I is used to measure the spatial agglomeration characteristics of adjacent spatially distributed objects (Su et al. 2019). The value of Moran's I range from -1 to 1 . A positive value indicates a positive spatial correlation, otherwise, it is a negative spatial correlation (Moran 1950). The global Moran's I show the overall correlation, and local analysis can be visualized in the form of cluster maps (Anselin 1995). The bivariate local Moran's I can characterize the spatial correlation between two different geographical data (Anselin et al. 2006). Hence, this study used the bivariate local Moran's I to explore the spatial agglomeration characteristics of GPI and GDP and analyzed their spatial matching patterns. GeoDa software was adopted to calculate the sustainability index values for each city. The calculation of the bivariate local Moran's I was as follows:

$$I_i^{KL} = \frac{x_i^K - \bar{X}_K}{\sigma^K} \sum_{j=1}^n \left[W_{ij} \frac{x_j^L - \bar{x}^L}{\sigma^L} \right]$$

where I_i^{KL} is the local spatial autocorrelation coefficient of city i 's GPI and GDP , and GPI and EF ; X_i^K represents GPI value of the city i ; X_j^L is GDP or EF value of the city j ; σ^K represents the variance of GPI , σ^L represents the variance of GDP or EF ; and n is the number of cities.

Cluster analysis

Cluster analysis is a major statistical analysis method for studying classification (samples or indexes) and is also an important algorithm for data mining. Cluster analysis usually consists of multiple patterns, such as measurement ranges or points in a multidimensional space (Shahrivari and Jalili 2016). The k -means algorithm is a widely used clustering method (Jain 2010; Ye et al. 2020), which was employed to divide 27 cities into k clusters according to the similarity of indicators. The values of ES and GEE were normalized by the z -score method (Zheng et al. 2018), and all steps were implemented in SPSS Statistics 25 and GeoDa. The calculation steps were as follows (MacQueen 1967; Nielsen 2016):

Step 1: Appropriately select the initial centers of k categories to achieve optimal clustering. 27 cities were divided into 4 clusters according to the k -means algorithm.

Step 2: Calculate the Euclidean distance from any sample point to k centers, and classify the sample into the class of the center with the shortest distance;

$$\|x_i - s_j\| < \|x_i - s_p\|, p = 1, 2, \dots, k, j \neq p, j \in \{1, 2, \dots, k\}$$

where x_i includes two variates ES and GEE within block i .

Step 3: Update new cluster center $s_1^*, s_2^*, \dots, s_k^*$ through the mean value method;

$$s_j^* = \frac{1}{n} \sum_{x_i \in \xi_j} x_i$$

where n is the number of elements in cluster S_i .

Step 4: Repeat steps 2 and 3 until there is no change for all k cluster centers.

Results

Temporal variability of GPI, ES, and GEE

From 2000 to 2018, GPI per capita increased exponentially (Fig. 3a). In terms of provinces, the GPI per capita of Shanghai and Zhejiang were the top two, and the GPI per capita of Jiangsu Province was similar to the average of the four provinces. However, the GPI per capita of Anhui Province lagged behind that of other provinces. In terms of cities, the higher the slope, the faster the growth rate of GPI per capita from 2000 to 2018 (Fig. 3b). Tongling, Hefei, Taizhou, Nanjing, and Ningbo had a ratio of GPI in 2018 to GPI in 2000 higher than 3.5, which was a higher growth rate than others. According to GPI per capita in 2018, the cities with low GPI per capita were Jinhua, Anqing, and Yangzhou. GPI per capita of these cities was all below \$4000 (2015 US\$). However, cities with GPI per capita higher than \$7000 were Hangzhou, Ningbo, Shanghai, Changzhou, Wuxi, Suzhou, Taizhou, and Hefei.

From 2000 to 2018, ES showed a downward trend and gradually stabilized, which indicated that the growth rate of genuine progress was slower than that of GDP. In terms of provinces, the ES value of Anhui Province was high, while that of other provinces remained relatively low (Table 2). In terms of cities, the GPI per capita of most cities was lower than GDP per capita, and only a few cities such as Chuzhou, Chizhou, Anqing, and Xuancheng had GPI per capita slightly higher than their GDP per capita from 2000 to 2005. Since 2000, the ES of most cities had fluctuated steadily between 0.2 and 0.5. By calculating ES in 2018, it was found that cities with higher ES were Chuzhou, Xuancheng, Chizhou, Anqing, and Taizhou, and ES of these cities was above 0.5. Yangzhou, Suzhou, Zhoushan, Wuxi, Jinhua, Zhenjiang, Nanjing, Changzhou, Jiaying, and Nantong were cities with the ES below 0.3.

GEE showed an overall upward trend from 2000 to 2018. In terms of provinces (Fig. 4a), the GEE of Shanghai was much higher than the other provinces. Zhejiang Province

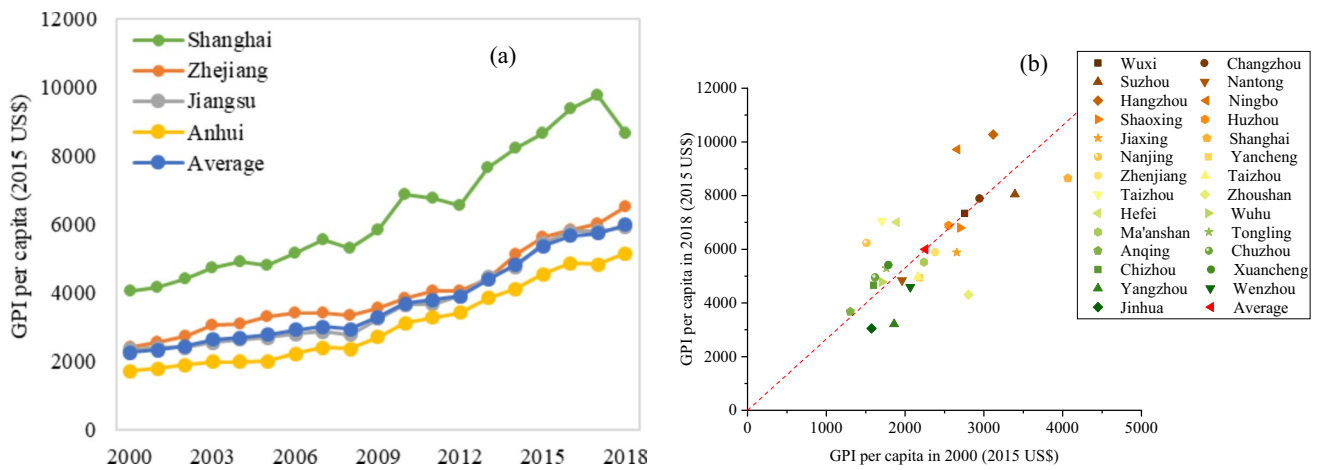


Fig. 3 a The GPI per capita at the province scale from 2000 to 2018. b The ratio of GPI in 2018 to GPI in 2000 of 27 cities, GPI per capita was in 2015 US\$

Table 2 The values of *ES* of cities. The background color of each value was graded by the conditional formatting tool in Excel. The darker the red (blue), the larger (smaller) the *ES* value

Province	City	2000	2003	2006	2009	2012	2015	2018	
Anhui	Hefei	0.74	0.57	0.53	0.45	0.49	0.53	0.41	
	Wuhu	0.81	0.75	0.56	0.41	0.39	0.40	0.38	
	Ma'anshan	0.64	0.54	0.37	0.29	0.36	0.50	0.44	
	Tongling	0.29	0.34	0.23	0.38	0.46	0.74	0.50	
	Anqing	1.07	0.93	0.62	0.68	0.64	0.70	0.68	
	Chuzhou	1.04	1.09	0.96	0.91	0.86	0.82	0.84	
	Chizhou	1.35	1.21	0.96	0.82	0.67	0.76	0.74	
	Xuancheng	1.07	1.00	0.93	0.91	0.80	0.79	0.77	
Jiangsu	Nanjing	0.26	0.25	0.14	0.24	0.18	0.30	0.28	
	Wuxi	0.34	0.26	0.20	0.19	0.19	0.23	0.21	
	Changzhou	0.55	0.47	0.40	0.34	0.30	0.30	0.29	
	Suzhou	0.42	0.27	0.19	0.16	0.18	0.21	0.20	
	Nantong	0.70	0.47	0.37	0.34	0.30	0.34	0.29	
	Yancheng	0.96	0.67	0.47	0.46	0.44	0.54	0.50	
	Yangzhou	0.59	0.39	0.35	0.25	0.19	0.26	0.18	
	Zhenjiang	0.49	0.45	0.28	0.28	0.23	0.26	0.26	
	Taizhou	0.90	0.67	0.43	0.42	0.38	0.39	0.32	
	Zhejiang	Hangzhou	0.46	0.45	0.37	0.36	0.32	0.37	0.41
		Ningbo	0.42	0.35	0.25	0.26	0.24	0.36	0.37
		Wenzhou	0.61	0.53	0.43	0.38	0.37	0.38	0.43
		Shaoxing	0.54	0.41	0.40	0.36	0.33	0.40	0.38
		Huzhou	0.66	0.63	0.48	0.44	0.39	0.45	0.45
Jiaxing		0.55	0.44	0.32	0.34	0.34	0.32	0.29	
Jinhua		0.46	0.30	0.22	0.18	0.15	0.25	0.24	
Taizhou		0.50	0.74	0.64	0.54	0.49	0.64	0.60	
Shanghai	Zhoushan	0.75	0.63	0.43	0.34	0.28	0.28	0.21	
	Shanghai	0.45	0.43	0.38	0.43	0.45	0.51	0.43	
Total	Average	0.65	0.56	0.44	0.41	0.39	0.45	0.41	

was second, followed by Anhui and Jiangsu. The GEE of most cities was on the rise. Overall, the natural resource efficiency of most cities has increased since 2000. Especially

since 2013, the growth rate of GEE has accelerated. The ratio of GEE in 2018 to GEE in 2000 of Taizhou, Chuzhou, Hangzhou, Nanjing, and Tongling was higher than

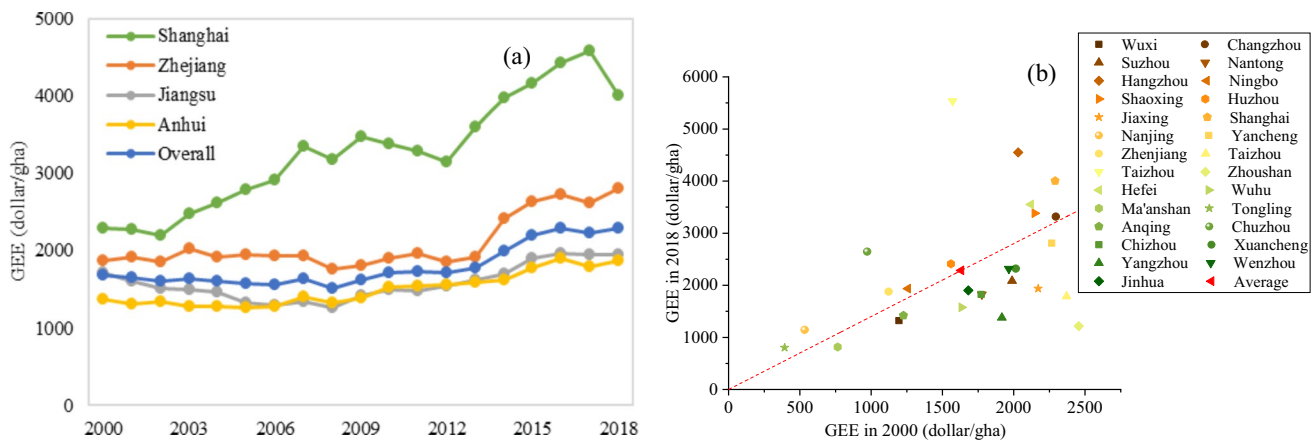


Fig. 4 **a** The average of GEE by province in 2000–2018. **b** The ratio of GEE in 2018 to GEE in 2000 of 27 cities

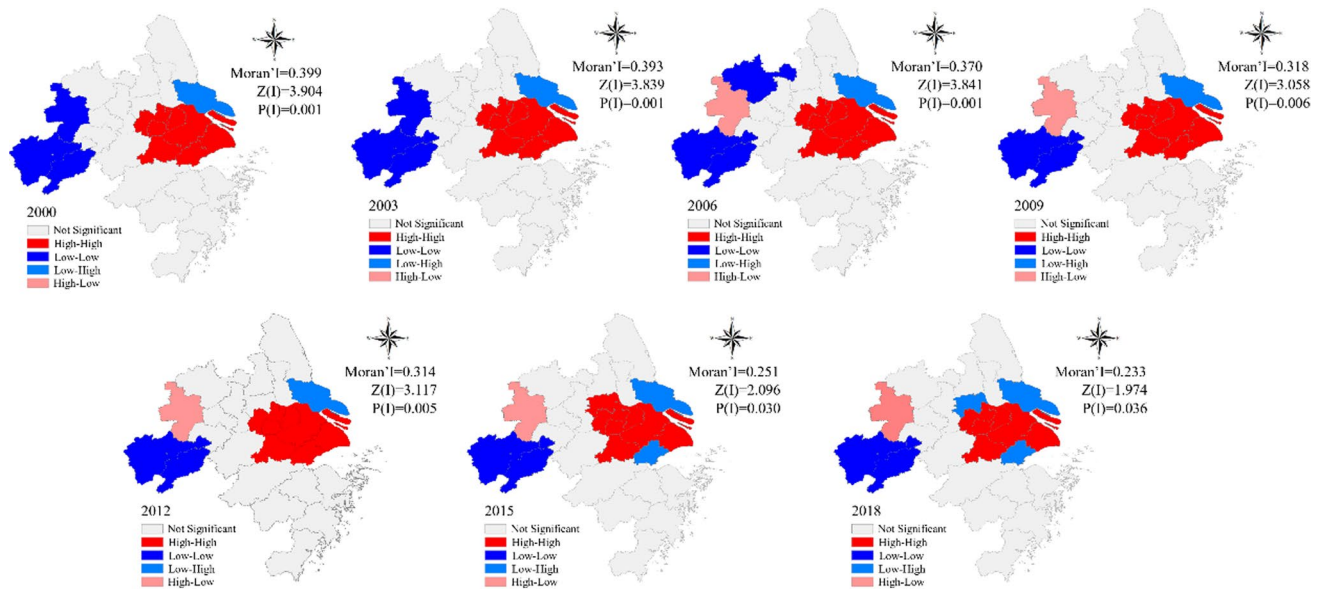


Fig. 5 Spatial patterns of the GPI and GDP in the Yangtze River Delta from 2000 to 2018 (the first high or low represents the value of GPI, and the second high or low represents the value of GDP)

2, and their growth rate was higher than that of other cities (Fig. 4b). The cities with high GEE in 2018 were Taizhou, Hangzhou, Shanghai, Shaoxing, Hefei, and Changzhou, whose values were all above \$3000/gha. However, the cities with low GEE in 2018 were Ma'anshan, Tongling, and Nanjing, whose values were all below \$1200/gha.

Spatial variability of GPI

Spatial variability of GPI and GDP

The LISA maps (Fig. 5) demonstrate a specific spatial pattern of GPI and GDP from 2000 to 2018. The Moran's I of GPI and GDP dropped from 0.399 to 0.233. It reached the highest value

in 2000, and its confidence coefficient reached 95%, suggesting a strong agglomeration effect ($Z(I) > 1.96$, $P(I) < 0.05$).

The results showed that there were many stable high-high (high GPI and high GDP) clusters. The numbers of low-low (low GPI and low GDP) clusters, low-high (low GPI and high GDP), and high-low (high GPI and low GDP) clusters were small and varied greatly over time. (1) The high-high clusters were hot spots which were mainly located in the eastern cities, consisting of Shanghai, Suzhou, Wuxi, Huzhou, Changzhou, and Jiaxing. (2) As cold spots, the low-low clusters were mainly located in the western inland of the Yangtze River Delta, consisting of Anqing, Hefei, and Chuzhou. (3) Nantong was in the low-high cluster from 2000 to 2018, but Zhenjiang and Jiaxing transitioned from high-high

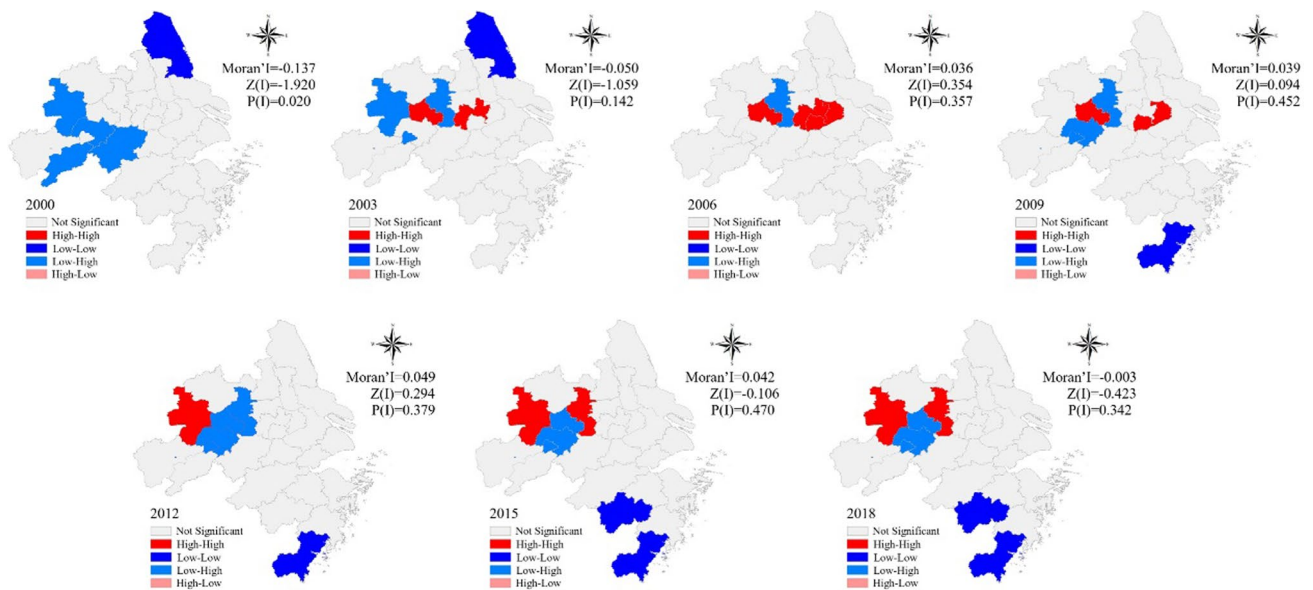


Fig. 6 Spatial patterns of the GPI and EF in the Yangtze River Delta from 2000 to 2018 (the first high or low represents GPI, and the second high or low represents EF)

cluster to low–high cluster. (4) The high-low clusters have situated northwest of the Yangtze River Delta. Hefei was a typical city in the high-low cluster.

Spatial variability of GPI and EF

The LISA maps (Fig. 6) showed that the Moran's I values of GPI and EF were positive or negative, and the Moran's I values were not significant from 2000 to 2018 ($Z(I) > 1.96$, $P(I) < 0.05$), showing that the genuine economic development and natural resources consumption in the Yangtze River Delta presented a spatially random distribution. In general, the genuine economic development and natural resource consumption in the Yangtze River Delta had no spatial spillover and interaction effects, reflecting that the economy of the cities was seldom affected by the surrounding environment.

Overall spatial patterns between ES and GEE

The study further classified and summarized the economic sustainability and ecological efficiency of the 27 cities in the Yangtze River Delta to put forward governance suggestions for urban development. According to GEE and ES in 2018, the 27 cities in Yangtze River Delta were mainly divided into four categories by k -means cluster analysis: high-high cluster (high ES and high GEE), low–high cluster (low ES and high GEE), low-low cluster (low ES and low GEE), and high-low cluster (high ES and low GEE) (Fig. 7).

Hangzhou, Shanghai, and Taizhou in the high-high cluster were mainly provincial capitals and coastal cities, and their economic development and ecological efficiency were

relatively high. There are 14 cities in the Yangtze River Delta located in the low-low cluster, revealing that most cities had low genuine ecological efficiency and low economic sustainability. The high-low cluster was mainly located in the west of the Yangtze River Delta, including Anqing, Chizhou, Xuancheng, and Chuzhou, and its ecological efficiency was low. Yancheng, Hefei, Changzhou, Huzhou, Shaoxing, and Wenzhou were the main cities in the low–high cluster. From the above analysis, it can be seen that most cities in the Yangtze River Delta were located in high-high and low-low clusters.

Discussion

Is the Yangtze River Delta urban agglomeration economically sustainable?

This study adopted GPI indicators to explore the development mechanism of the Yangtze River Delta from a spatiotemporal perspective. The results indicated that the cities of the Yangtze River Delta had two distinct growth phases of GPI per capita since 2000: the GPI in phase I (2000–2005) did not change much, and GPI per capita in phase II (2006–2018) increased rapidly, which was consistent with the results of previous studies (Wen et al. 2008; Huang et al. 2016). It showed that the social welfare of the urban agglomeration has been significantly improved since 2006. However, ES of most cities in the Yangtze River Delta had decreased over time, indicating that the negative contributions, such as environmental damage, unequal income distribution, and cost of family breakup, exceed the positive

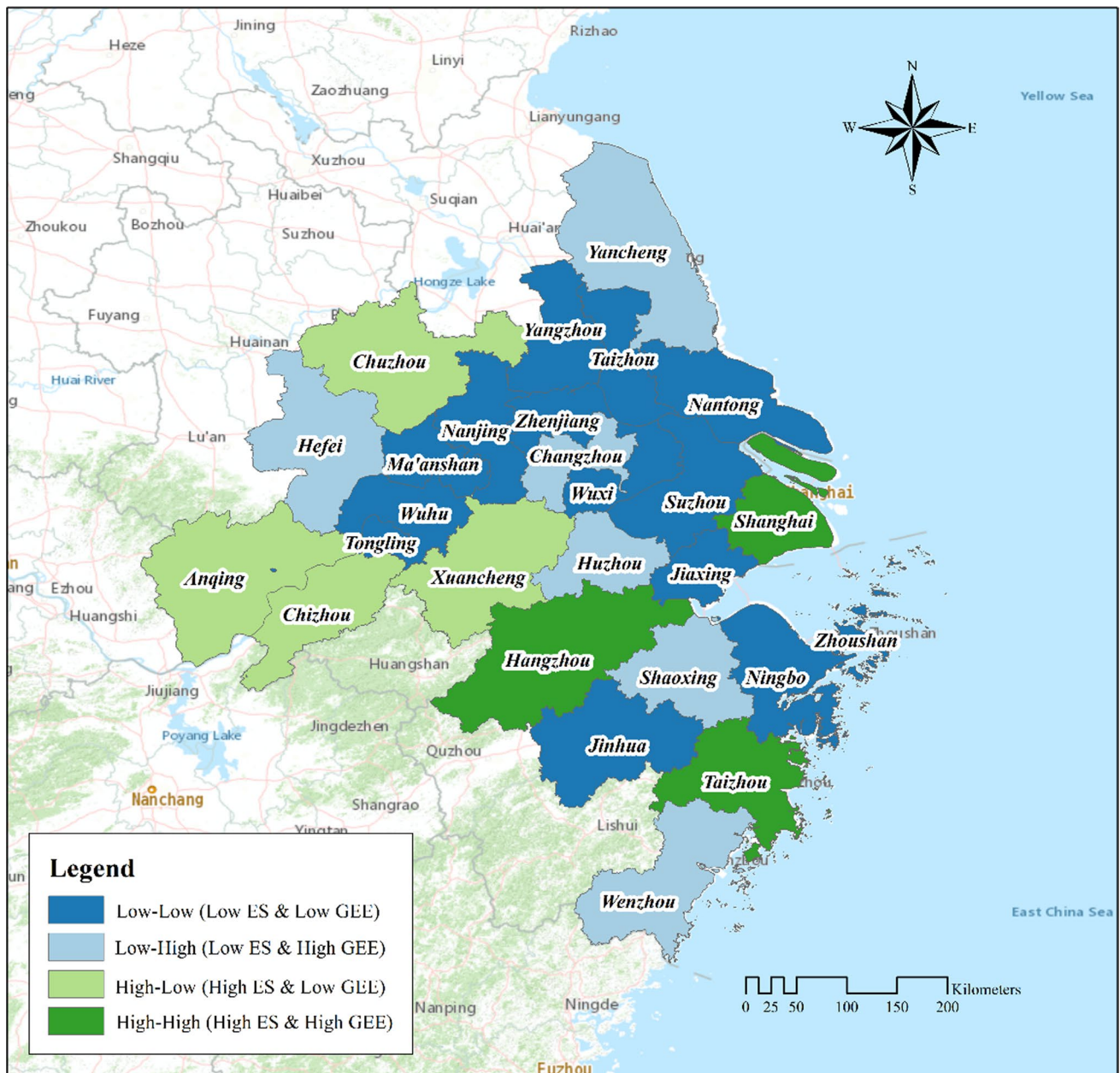


Fig. 7 Cluster analysis based on ES and GEE

contributions (Danish and wang Z. 2019). The improvement of social welfare lagged behind economic growth and fully reflected the “relative threshold effect” (Long and Ji 2019). This was consistent with other sustainability assessments in the Yangtze River Delta. Although the sustainability of the Yangtze River Delta gradually improved, it still needed to be improved and strengthened (Li and Li 2017; Xu et al. 2021; Zhong et al. 2021). It should be noted that the ES of Anhui Province was higher than that of the other three provinces. The main reason was that the GDP per capita of Anhui Province was relatively low, and the GPI was not far behind the other three provinces. Besides, Jiangsu Province

is currently in an unsustainable state as the resource consumption required by residents has exceeded the environmental capacity (Peng et al. 2019).

The GPI and GDP of the Yangtze River Delta had obvious spatial characteristics. The spatial relationship between GPI and GDP is the result of the positive effects of economic agglomeration. Areas with rapid economic development are prone to spatial agglomeration, and economic agglomeration can produce positive effects and spatial spillover effects, such as reducing transportation costs and improving technology (Zeng and Zhao 2009; Tao et al. 2020). Suzhou, Wuxi, and Changzhou, as the hot spots for GPI and GDP correlation

analysis, established the “Suzhou-Wuxi-Changzhou Metropolitan Area” in 2003 to strengthen the economic function and its interaction with Shanghai. The Suzhou industrial park, one of the most developed areas in China, has been constructed to facilitate the development of advanced manufacturing and modern service industry clusters. Meanwhile, Shanghai is dominated by a digital economy and has a high level of science and technology. Knowledge spillovers are more likely to occur in the surrounding areas of Shanghai (Jin et al. 2020). The economic activities in Shanghai are highly concentrated, making important contributions to the economic development and the improvement of the quality of life (Long and Ji 2019). On the contrary, cities in Anhui Province were mainly distributed in cold spot regions, and their economic development lagged far behind other cities. The province should strengthen the protection of the environment, and pay more attention to the quality of economic growth, thus forming a steady-state economy (Daly 2014).

Is the Yangtze River Delta urban agglomeration ecologically efficient?

Since 2000, GEE has continued to rise, and the natural resources efficiency has gradually increased, which is in line with the results of other studies (Yang and Yang 2019; Liu et al. 2021). Studies have shown that technological progress is the decisive factor for improving China’s ecological efficiency, and poor management is the main obstacle restricting the improvement of ecological efficiency (Yang and Zhang 2018). Government management has made certain progress. For example, a series of laws and regulations have been formulated, such as “management methods of ecological environment standards,” to provide policy guarantee for strengthening the supervision and management of enterprises and ensure the quality of industrial economic development (Ministry of Ecology and Environment of People’s Republic of China 2020). To promote the sustainable development of cities, the government should firmly establish an innovative, coordinated, green, open, shared development strategy, continue to improve technological innovation, and promote the transformation and upgrading of traditional industries.

The study showed that no spatial relationship exists between genuine economic development and ecological resource consumption. Regions with high ecological efficiency have not formed regional clusters. This is mainly due to the different development stages of cities, which may be related to the resource utilization policies and protection efforts of each city. As provincial capitals, Shanghai, Hangzhou, and Hefei had high ecological efficiency. They had played a leading role in each province and shown a promising direction for subsequent cities in the province. However, as the capital of Jiangsu Province, the GEE value of Nanjing is much lower than that of other capital cities because of

ecological efficiency. There is an urgent need to strengthen the promotion of related technologies and policy support.

Recommendations for urban development

In this study, two-thirds of the cities are located in the high-high cluster and low-low cluster. It reasonably explains the positive impact of economic sustainable development and contributes to the effective use of ecological resources (Danish et al. 2019). Studies showed that technological innovation and resource consumption are important mechanisms of environmental regulation that affect economic growth (Cao et al. 2020). The improvement of the economic growth quality promotes technological innovation, which in turn increases productivity and reduces resource consumption. The combination of ES and GEE was an attempt in ecological economics research considering environmental, social, and economic factors and could provide directions for cities at different development stages.

(1) High-high cluster (high ES and high GEE): The cities in high-high areas of the Yangtze River Delta were conducive to promoting the sustainable development of the society. Shanghai and Hangzhou were typical cities of the high-high cluster, which were the center of the Yangtze River Delta and capital city of Zhejiang Province, respectively. From the *k*-means cluster analysis, they had better social welfare and higher ecological resource efficiency. Spatial aggregation of economic activities existed in various cities, so economic network effects were of vital importance (Zhang et al. 2021). The cities in high-high areas could provide technical support, strengthen cooperation for surrounding cities, and improve the economic development of the region.

(2) Low-high cluster (low ES and high GEE): low-high areas had lower economic sustainability and higher ecological efficiency. It showed that in these cities, economic development did limited damage to the environment, and local GDP per capita was relatively high. However, social factors such as the cost of family breakup and the cost of crime affected the quality of economic growth. The local government could focus on promoting employment and entrepreneurship, strengthening all-around employment services, and steadily increasing the income level for residents. Urban and rural subsistence allowances should be steadily increased to improve people’s livelihood. Meanwhile, the public legal service system should be improved, the security of society should be maintained, and the people’s sense of happiness and sense of gain should be improved.

(3) Low-low cluster (low ES and low GEE): Most cities in the Yangtze River Delta were in low-low areas. The economy of these cities was originally weak or affected by industrial pollution in the early stage. For example, the ecological efficiency of Tongling and Ma’anshan, where heavy industry was the major industry, was much lower than that of surrounding cities. The government should actively guide to

transform heavy industries into energy-saving and environment-friendly industries, and prevent excessive energy consumption by strengthening energy management strategies (Ji and Long 2016; Danish and wang Z. 2019). Tongling could take the copper-based new material industry, and Ma'anshan could vigorously promote the optimization and upgrading of traditional industries. It is necessary to strengthen economic agglomeration and green development, and further improve the efficiency of natural resource utilization.

(4) High-low clusters (high ES and low GEE): high-low clusters, including Chuzhou, Xuancheng, Chizhou, and Anqing in Anhui province, had high ecological pressures. Studies showed that the environmental quality of Anhui province was in a poor state, the relationship between the supply and demand of environmental consumption was unbalanced, and the energy consumption structure was unsustainable (Miao et al. 2016). These cities need to be significantly committed to ecological compensation and ecological restoration (Li et al. 2009; Wei et al. 2015) and to strengthen environmental protection in an all-around way to avoid economic development at the expense of the environment (Usman et al. 2021). Implement the property rights system of natural resource assets to regulate the use and management. The utilization and carrying capacity of natural resources should be improved in terms of technology to alleviate environmental pressure to build environment-friendly cities.

Conclusions

This study adopted GPI, integrating with GDP and EF, to evaluate economic sustainability and ecological efficiency, which covered environmental, economic, and societal factors. It demonstrated that GPI and GEE increased rapidly, but ES showed a downward trend and gradually stabilized. GPI and GDP had a high degree of spatial correlation, especially in Suzhou-Wuxi-Changzhou Metropolitan Area. Shanghai, Hangzhou, and Taizhou were cities with the highest level of economic sustainability and ecological efficiency. The results indicated that the rapid economic growth promoted the improvement of social welfare. However, the social welfare and economic growth rate did not match, and the economic sustainability of the Yangtze River Delta should be further improved. The cities could optimize the economic structure, improve social welfare and economic growth at the same time, and achieve economic sustainability by developing environmental regulations, carrying out green technological innovation, and increasing the rate of resource utilization. Besides, economic agglomeration should be encouraged to realize the sharing of knowledge and resources. The research provided theoretical references for decision-makers to implement policies for alleviating ecological pressure and promoting economic sustainable development of the Yangtze River Delta agglomeration.

Appendix

Please see Table 3

Table 3 Description of indicators and methods of GPI

Dimensions and objectives	Indicators	Description and method	Contribution	Data source
Economy <i>In order to measure people's consumption expenditure and income based on income equality</i>	Personal consumption expenditures	Personal consumption expenditure is the initial indicator for calculating GPI. The more personal consumption expenditure, the better the social welfare	+	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Adjustment for unequal income distribution (for rural residents)	$Personal\ consumption\ expenditures = Total\ consumption\ expenditure / Total\ population$ We use the Gini coefficient to derive an index reflecting income inequality and use 2000 as the base year. The higher the degree of fairness of distribution, the higher the level of GPI (Wen et al. 2007)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Adjustment for unequal income distribution (for urban residents)	We use the Gini coefficient to derive an index reflecting income inequality and use 2000 as the base year. The higher the degree of fairness of distribution, the higher the level of GPI (Wen et al. 2007)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of consumer durables	Cost of consumer durables refers to the purchase of consumer durables that have a long service life and can generally be used multiple times, such as household appliances and furniture	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Services of consumer durables	$Cost\ of\ consumer\ durables = Cost\ of\ consumer\ durables\ of\ urban\ residents \times Urban\ population + Cost\ of\ consumer\ durables\ of\ rural\ residents \times Rural\ population$ We adopt the same assumption as (Long and Ji 2019) that the average of services of consumer durables is 8 years, so the depreciation rate is 12.5% per year $Services\ of\ consumer\ durables = Cost\ of\ consumer\ durables \times Depreciation\ rate$	+	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook

Table 3 (continued)

Dimensions and objectives	Indicators	Description and method	Contribution	Data source
Society <i>In order to comprehensively evaluate the economic benefits generated by divorce and other activities that cause social problems, as well as the economic costs in response to the decline in the quality of life caused by crimes, car accidents and other factors</i>	Cost of crime	We take the sum of government expenditures in the Public Security, Procuratorate, and Judicial Department and family property insurance payments as the cost of the crime	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of automobile accidents	Costs of automobile accidents can be directly obtained from statistical yearbooks	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of commuting	Commuting costs include economic costs (non-entertainment expenditures on transportation) and time costs. The economic cost mainly adopts the (Cobb 1995) method, and the time cost is the commuting time multiplied by the wage rate (Costanza et al. 2004)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of family breakup	The cost of family breakup refers to a series of costs incurred by divorce. Studies have shown that the unit cost of divorce in China is US\$20,427 (Costanza et al. 1997; Long and Ji, 2019; Wen et al. 2007)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of underemployment	$Cost\ of\ family\ breakup = Unit\ cost\ of\ each\ divorce \times Number\ of\ divorces$ The cost of underemployment refers to the economic losses caused by people losing their jobs $Cost\ of\ underemployment = (Monthly\ minimum\ wage - Minimum\ living\ guarantee\ standard\ for\ urban\ residents) \times Total\ unemployment \times 12\ months$	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Change of leisure time	The value of leisure time mainly refers to the social welfare produced by leisure time $Change\ of\ leisure\ time = Number\ of\ leisure\ days\ per\ year \times Average\ salary\ of\ employees \times Number\ of\ employees\ at\ the\ end\ of\ the\ year$	+	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Value of housework and parenting	The unit value of housework and parenting is measured by the wage rate of housework $Value\ of\ housework\ and\ parenting = Housework\ time\ per\ family \times Number\ of\ households \times hourly\ wage\ in\ the\ labor\ market$	+	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Value of volunteer work	The value of volunteer work refers to the social welfare generated by people through voluntary services, such as community volunteer service $Value\ of\ volunteer\ work = Volunteer\ service\ time \times Prices\ in\ the\ local\ service\ market$	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of pollution (air pollution is excluded)	The cost of pollution refers to the cost of environmental treatment, which can be obtained directly from the statistical yearbook	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
	Cost of air pollution	The cost of air pollution mainly includes the environmental cost of SO ₂ , total suspended particles (TSP), and CO ₂ The unit environmental costs of SO ₂ and TSP are 1250/t CNY and 109/t CNY, respectively. The unit environmental cost of CO ₂ is 48/t CNY (Long and Ji 2019)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook
Environment <i>In order to comprehensively measure the environmental costs of economic activities and evaluate the consumption of natural resources</i>	Change of wetlands	The change of wetlands indicates the amount of increase (decrease) in the wetlands. The unit cost of wetland loss is estimated at \$14,785/ha (Costanza et al. 1997) $Change\ of\ wetlands = Increase\ (Decrease)\ in\ wetland\ area \times The\ unit\ cost\ of\ wetland\ loss$	-	China Environmental Statistics Yearbook Institute of Geographical Sciences and Natural Resources Research of Chinese Academy of Sciences
	Change of farmland	Change of farmland indicates the amount of increase (decrease) in the farmland. The unit cost of farmland loss is estimated at \$35,640/ha CNY $Change\ of\ farmland = Increase\ (Decrease)\ in\ farmland\ area \times The\ unit\ cost\ of\ farmland\ loss$	-	China Environmental Statistics Yearbook Institute of Geographical Sciences and Natural Resources Research of Chinese Academy of Sciences
	Change of forest	Change of forest indicates the amount of increase (decrease) in the forest. The unit cost of forest loss is estimated at \$969/ha (Costanza et al. 1997) $Change\ of\ forest = Increase\ (Decrease)\ in\ forest\ area \times The\ unit\ cost\ of\ forest\ loss$	-	China Environmental Statistics Yearbook Institute of Geographical Sciences and Natural Resources Research of Chinese Academy of Sciences
	Depletion of nonrenewable resources	GPI calculates the consumption of nonrenewable resources as costs. We apply the net price method to estimate the depletion of nonrenewable resources (Long and Ji 2019)	-	Shanghai Statistical Yearbook, Zhejiang Statistical Yearbook, Jiangsu Statistical Yearbook, Anhui Statistical Yearbook

+ indicates a positive impact on GPI; - indicates a negative impact on GPI

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