

Exploring complex urban growth and land use efficiency in China's developed regions: implications for territorial spatial planning

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Abstract Developed regions in China have experienced rapid urban expansion and have consequently induced a series of challenging environmental issues since its economic reform and opening-up. Taking Zhejiang as a case study area, the present paper explores the complex types of urban growth over the last four decades as well as land use efficiency. Moreover, it discusses the implications of the aforementioned on China national territorial spatial planning (TSP). The acquired results have shown that: 1) urban expansion has slowed down, exhibiting a three-stage trend of “slight increase (1980–1990)—dramatic growth (1990–2010)—slow growth (after 2010)”; 2) the complex types of urban growth reveal that the urban diffusion has been gradually controlled and the urban form tends to be more condensed; and 3) the mean values for pure technical efficiency (PTE) and scale efficiency (SE) of urban land use are 0.83 and 0.95 respectively, indicating PTE as the main factor restricting the improvement of urban land use. Based on these results, some beneficial policy implications and suggestions for TSP are provided. First, it is suggested that “Inventory Planning” will be the main direction of TSP other than “Incremental Planning”. Secondly, we should pay more attention to the protection of cultivated land and ecological resources. Lastly, TSP should guide the economic growth away from simply relying on resource inputs and steer it toward technology and capital investment.

Keywords urban expansion, urban growth types, land use efficiency, Zhejiang, territorial spatial planning

1 Introduction

As the largest developing country in the world, China has

experienced unprecedented rapid socio-economic since the reform and opening up in 1978 (Du et al., 2019). This process was accompanied by an important land use change-conversion of large rural areas into urban areas, a process known as urban expansion (Zhang and Xu, 2017). The rapid urban expansion significantly altered the land surface cover and has consequently induced a series of challenging environmental issues (e.g., regional climate change, biodiversity loss, carbon cycle, etc.) (DeFries et al., 2010; Tan et al., 2015; Li and Gong, 2016). This problem is far more severe in China's developed regions, as they have witnessed the greatest population pouring from rural areas and less developed regions to the urban areas (United Nations, 2019). Therefore, it is crucial to understand the evolving dynamics of urban expansion in China's developed regions and map out specific development policies to evade, mitigate, and solve social and environmental problems caused by urbanization.

There is no universally accepted definition of the term “urban”, nor is there a distinct boundary that separates the urban areas from the non-urban areas in the real world (Brenner and Schmid, 2014). As of the present, governments have heavily relied on country-specific administrative boundaries that are mainly divided by historical, political, and geo-graphical reasons (Wang et al., 2021). Chinese cities often function as a political-administrative unit enveloping a domain much larger than just the urban areas. Rather, they include an urbanized core surrounded by extensive rural areas. Remote sensing is a powerful tool that can be used to monitor transformation in urban characteristics (e.g., multispectral information, light emissions, and morphological structures) (Zheng et al., 2020; Li et al., 2021). Although multi-source global land cover data and nighttime-light data (e.g., MODIS500m and NPP-VIIRS500m) have been widely used for the delimitation of urban areas at the global and regional scales, but their qualities are far from satisfactory

Received September 15, 2021; accepted January 21, 2022

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(Schneider et al., 2010; Wu et al., 2018). A potential solution for improving the delimitation of urban areas would be to discern urban characteristics from the finer resolution data (Kew and Lee, 2013; Peng et al., 2018; Corbane et al., 2019). Landsat-based global land cover product-GlobeLand30 has been released three periods (2000, 2010, and 2020) for open access and non-commercial utilization (available at National Geomatics Center of China website), providing an alternative to delimiting urban areas. As a land cover type of GLOBELAND30, the artificial surfaces are primarily based on asphalts, concrete, sand and stone, bricks, glasses, and other materials. In addition, they are more concentrated and contiguous than rural areas (Chen et al., 2015). Since the distribution of artificial surfaces can be easily and freely acquired from various land use and land cover production, we suppose it would be particularly helpful to develop a convenient method to delimit urban areas from the distribution of artificial surfaces.

In recent years, the Chinese government and its scholars have increasingly focused on controlling urban expansion. Additionally, scientific precepts aiming to alleviate the negative impacts on ecological environment in China have become a popular area of research (Cui et al., 2019; Ai et al., 2020; Zeng et al., 2021; Zhao et al., 2021). Urban land use efficiency (ULUE) reflects the ability to promote the synergic development of urban society, economy and environment. Scientific and reliable ULUE evaluation can serve as an important factor when deciding on the promotion of urban layout optimization (Liu et al., 2020; Tan et al., 2021). The methods of ULUE evaluation are primarily based on the input and output during land use, such as DEA model, SBM model and SFA model (Jia et al., 2017; Liu et al., 2020). Decomposing ULUE into pure technical efficiency (PTE) and scale efficiency (SE) for the purpose of analyzing influencing factors may provide in-depth explanations of land use allocation and management (Zhu et al., 2019).

The Chinese territorial spatial planning (TSP) refers to long-term planning and overall arrangement of land resources and spatial layout under the jurisdiction of the country or region government (Xinhua Agency, 2019a). From the periods of reform and opening up until now, Chinese TSP has gone through three stages (Liu and Zhou, 2021). The scientific use of land resources and promotion of agricultural development may be observed as the first stage. The promotion of the development of urbanization and industrialization is considered to be the second stage. The third stage refers to presently aiming to achieve high-quality and sustainable development by the new round of TSP (2020–2035). At present, the Chinese TSP has become an important tool in constructing ecological civilization.

In the present study, we selected Zhejiang, one of the most developed regions in China, for our case study. The process of urban expansion over the last four decades

were studied from both the perspectives of quantitative and spatial analysis to show the complex urban growth. Furthermore, the land use efficiency at the county level in Zhejiang was analyzed to reveal the existing problems of urban land use. The research results can provide a solid basis for scientific use of land resources and following these, some valuable suggestions on future Chinese TSP were discussed.

2 Materials and methods

2.1 Study area and data sources

Zhejiang is located along the southeastern coast of China (27°12'N–31°31'N, 118°01'E–123°10'E), with a total area of approximately 105500 km² and a GDP per capita of 14600 dollar, making it one of the smallest yet most developed provinces in China (Fig. 1). However, the habitable land resource in Zhejiang is extremely scarce, with the plains and basins accounting for only 23.2% of its total area. Since the implementation of China's reform and opening-up policy (1978), Zhejiang has witnessed rapid economic incline accompanied by an extensive increase in the urban population. The metropolitan population of Zhejiang reached 38.47 million in 2017. This is almost 3.8 times larger than the area's population in 1980. Likewise, the population-urbanization rate increased by 4.7 times to reach 68%. Therefore, the province of Zhejiang is considered to be an appropriate choice for analyzing the spatial-temporal trends of land urbanization in China's developed regions.

We acquired the land use maps from the project titled "National ecosystem survey and assessment of China (2000–2010)" and conducted by the Ministry of Ecology and Environment of the People's Republic of China (available at Resource Discipline Innovation Platform

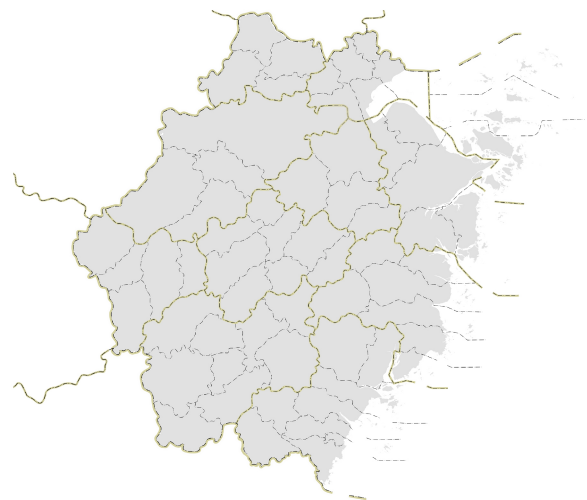


Fig. 1 Location of the study area DEM of Zhejiang.

website). In this project, Zhejiang produced land use maps with acceptable accuracy from the Landsat series of images in five periods (1970, 1980, 1990, 2000, and 2010). Additionally, the land use map for 2017 was produced by the same methods as were used in the present study. Based on this data, the artificial surfaces were extracted from land use maps to delimit urban areas. It must be emphasized that the urban green spaces were treated as artificial surfaces in this study in order to better display the urban morphology. We also acquired the data of the resident population and gross domestic product (GDP) for both 2010 and 2017 from Zhejiang Statistical Yearbook (available at Zhejiang Provincial Bureau of Statistics website).

2.2 Approach to delimit urban areas from the distribution of artificial surfaces

The approach taken in this study is conceptually simple as it defines urban areas as any area with a higher density of artificial surface (Fig. 2). Furthermore, this approach assumes that artificial surfaces in urban areas are denser than that in rural areas. The urban core may be detected by identifying the region with a high density of artificial surfaces. Kernel density estimation within a certain bandwidth is used to estimate a continuous spatial density of artificial surfaces.

First, the entire area of study was divided into a continuous hexagonal grid. Moreover, the density of the artificial surface, which was defined as the proportion of artificial surfaces within the bounds of the hexagonal cell, was evaluated for each cell. Hexagonal grids are advantageous due to their symmetric and invariant topology, which can be recursively partitioned either into a smaller division of grids or a larger amalgamation of them (Richards et al., 2000). Moreover, hexagonal grids can potentially reduce bias arising from edge effects (Birch et al., 2007). Second, urbanized cores were detected by kernel density estimation (KDE). To do this, a KDE

with an appropriate bandwidth was performed on the layer of the building density, representing the continuity of the artificial surfaces. We consider that the urban “hot spot” was the site with a higher KDE value. Due to the fuzzy and rough boundary of the urban “hot spot”, we repeated KDE with a finer bandwidth to delimit a more coincident boundary of the urban “hot spot”. Finally, spatial overlay analysis was performed on the layers of the urban “hot spot” and the “boundary” to delimit urban areas and to further indicate the urban artificial surfaces.

KDE is a non-parametric statistical tool used for estimating the probability distribution of an unknown random variable (Bailey and Gatrell, 1995). Furthermore, it may be used as a data smoothing tool employed to transform geographically referenced data points into a continuous surface. It has been widely used in density surface mapping and “hot spot” detection (Hu et al., 2018). Generally, the Rosenblatt-Parzen formulation described in Eq. (1) is most widely used for KDE computation:

$$f(x, y) = \frac{1}{nh} \sum_{i=1}^n k \left(\frac{\sqrt{(x-x_i)^2 + (y-y_i)^2}}{h} \right), \quad (1)$$

$$k(s) = \begin{cases} \frac{15}{16}(1-s^2) & |s| \leq 1 \\ 0 & |s| > 1 \end{cases}, \quad (2)$$

where $f(x, y)$ is the estimated value of probability density; h ($h > 0$) is the bandwidth of the estimation model, which represents the radius of the analysis neighborhood;

$\sqrt{(x-x_i)^2 + (y-y_i)^2}$ is the distance between the estimating site (x, y) and the sample site (x_i, y_i) out of all n sample sites in the analyzed region; and $k(s)$ is the kernel function, usually taken as the Quartic-Kernel-Function (Eq. (2)). The evaluation of KDE requires an input parameter termed the population field. This parameter represents the count or quantity to be spread across the landscape to

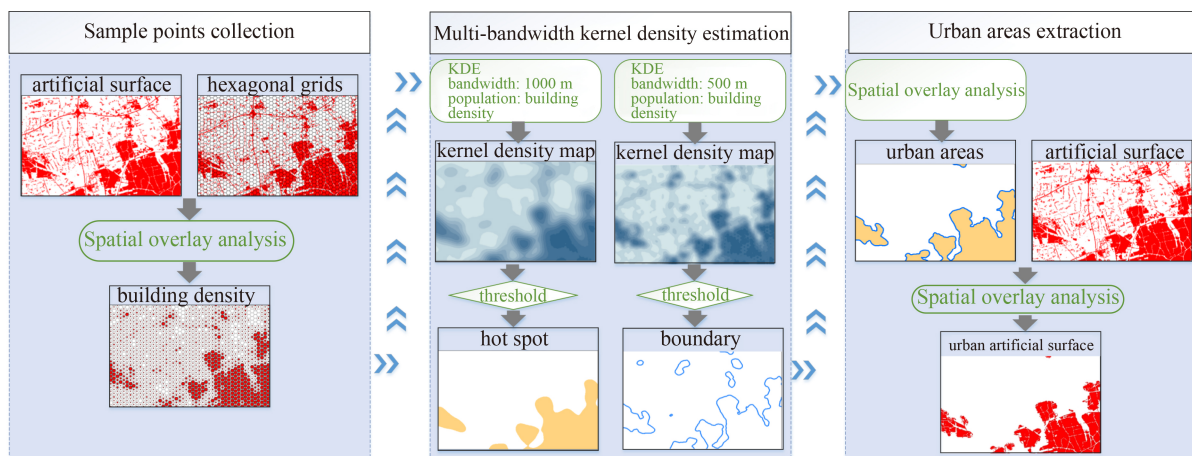


Fig. 2 Schematic representation of the urban area delimitation method.

create a continuous surface. In the present paper, the building density of each hexagonal center point was used as the population field.

2.3 Landscape metrics analysis

Complex spatial landscape characteristics can be externalized into identifiable patterns by using metric analysis. Previous studies have employed a restricted set of well-defined and measurable metrics to characterize landscape patterns that can effectively generate a vast amount of information (Su et al., 2014). In the present paper, a total of 5 land-scape-level metrics were selected to evaluate the size, complexity, and isolation of the urban areas. Total Area (*TA*) refers to the size of the urban area, which is expected to continuously increase as a result of the urbanization. Number of Patches (*NUMP*) represents the number of isolated patches which are expected to increase in the case of urban development or decrease if merged into a homogeneous patch. Mean Patch Area (*AREA_MN*) is a crucial index representing the degree of landscape fragmentation. A small value represents a high degree of fragmentation and vice versa. Moreover, the Area-Weighted Mean Shape Index (*AM_SHAPE*) quantifies the degree of the patches' complexity. The closer the value of *AM_SHAPE* is to 1, the simpler and more regular the shape is and vice versa. Area Weighted Mean Euclidean Nearest-Neighbor Distance (*AM_ENN*) is the most straightforward measure to quantify patch isolation. *AM_ENN* approaches 0 as the distance to the nearest neighbor decreases.

2.4 Mapping complex types of urban growth

Landscape expansion index (*LEI*) proposed by Liu et al. (2010) has been used to identify the growth types of the landscape. The complex types of urban growth can be divided into three categories, more specifically, the infilling type, the edge-expansion type, and the outlying type. The *LEI* (Eq. (3)) for a newly grown patch can be calculated by examining the proportion of the old patches within the buffer zone of the newly grown patch:

$$LEI = 100 \times \frac{A_0}{A_0 + A_V}, \quad (3)$$

where A_0 stands for the intersection between the buffer zone and the old patches, A_V is the intersection between the buffer zone and the vacant category. The growth pattern may be identified as the infilling type in case where *LEI* is greater than 50, as the outlying growth type when *LEI* is equal to 0, and as the edge-expansion type when *LEI* ranges from 0 to 50, respectively.

The area-weighted mean expansion index (*AWMEI*), which is an area-weighted mean *LEI* at the landscape level, is calculated to reflect the aggregate properties of the patch shown as Eq. (4):

$$AWMEI = \frac{\sum_{i=1}^N LEI_i \times a_i}{\sum_{i=1}^N a_i}, \quad (4)$$

where N is the total number of newly grown patches, and a_i is the area of this newly grown patch in Eq. (4). When the trend of landscape expansion is in the diffusion process, the value of *AWMEI* will be small. Conversely, the larger the *AWMEI* is, the more compact the landscape expansion will be.

2.5 Evaluating urban land use efficiency by 3-stage DEA model

To evaluate urban land use efficiency (ULUE), a 3-stage DEA model proposed by Färe and Grosskopf (1997) was applied. This model has been greatly improved with Data Envelopment Analysis technology. It comprises three stages.

2.5.1 Stage-1 the SBM-undesirable model

This model supposes that there to be multiple decision-making units (DMUs), where each DMU has m inputs (X) to produce n outputs (Y). In this scenario, λ represents the weight coefficient vector, while s^- stands for the input slack vector, and s^+ is the output slack vector. The SBM model that does not consider undesired outputs can be expressed as Eq. (5):

$$\rho = \min \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{s_i^-}{x_{i0}}}{1 + \frac{1}{n} \sum_{r=1}^n \frac{s_r^+}{y_{r0}}}, \quad \text{s.t.} \begin{cases} x_0 = X\lambda + s^- \\ y_0 = Y\lambda - s^+ \\ \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \end{cases}, \quad (5)$$

where ρ is the efficiency value; x_0 is the input vector of the DMU to be evaluated; y_0 is the output vector of the DMU that is to be evaluated; s_i^- , s_r^+ represent the slack values of the i -th input indicator and the r -th output indicator, respectively.

2.5.2 Stage-2 Stochastic Frontier Analysis

The efficiency value of the Stage-1 DEA model is affected not only by internal management factors but also by external environmental factors and stochastic errors. It is therefore necessary to divest the external environmental factors and stochastic errors on the efficiency value. For this, Timmer and Los (2005) proposed the Stochastic Frontier Analysis (*SFA*). The n -th input value of the i -th DMU is taken to be x_{ni} , while the slack variables s_{ni} are $s_{ni} = x_{ni}$, $x_{ni}\lambda > 0$. The regression equation is set to

$$s_{ni} = f(Z_i, \beta_n) + V_{ni} + U_{ni} \quad n = 1, 2, \dots, N; \quad i = 1, 2, \dots, I, \quad (6)$$

where s_{ni} is the slack variable for the n -th input of the i -th decision-making unit; $f(Z_i, \beta_n)$ represents the effect of the environment variable on the slack variable; $V_{ni} + U_{ni}$ is the mixed error term.

The environmental factors and impact of stochastic errors can be stripped with

$$x_{ni}^* = x_{ni} + [\max\{Z_i\beta^n\} - Z_i\beta^n] + [\max\{V_{ni}\} - V_{ni}], \quad (7)$$

$$n = 1, 2, \dots, N; \quad i = 1, 2, \dots, I$$

where x_{ni}^* is the adjusted input amount, and x_{ni} is the input value from Stage-1.

2.5.3 Stage-3 the adjusted DEA model

The adjusted input data and original output data obtained in Stage-2 are once more brought into the SBM-undesirable model. This is done in order to calculate the pure technical efficiency value, which is now free of environmental factors and stochastic factors.

The present study aims to evaluate the efficiency of urban land use on economic development. Considering the availability of the indices, we defined the land, capital, and labor as input indices, represented by the amount of urban areas, the total fixed asset investment, and the number of employees in the secondary and tertiary industries, respectively. In addition, economic benefits were selected as output indices. They were represented by the GDP of the secondary and tertiary industries and by the disposable income of urban residents. Urbanization does not solely represent the dynamic factor but the process of land use as well. Therefore, the urbanization rate was input as an environment variable.

3 Results

3.1 Urbanization process in Zhejiang from 1980 to 2017

In the period of 1980 to 2017, the urban area in Zhejiang increased by 6594 km² with an annual increase of 178.2 km². Table 1 shows the expansion rate and annual expansion area of Zhejiang’s urban areas with respect to the four periods. During the period of 1980–1990, the annual expansion area was considered to be 31.9 km² at an expansion rate of 23%. The annual expansion area increased to 172.9 km² with an extremely fast growth rate

Table 1 The expansion rate and annual expansion area of Zhejiang’s urban area in the four periods

	1980–1990	1990–2000	2000–2010	2010–2017
Expansion rate	23%	100%	89%	22%
Annual expansion area/km ²	31.9	172.9	307.9	209.6

of 100% during the period between 1990 and 2000. Furthermore, the largest annual expansion area was 307.9 km² during the period of 2000–2010. Finally, during the period of 2010–2017, the expansion rate showed signs of slowing down, as the annual expansion area was decreasing to 209.6 km².

The term resident population-urbanization represents the migration of people from country to city. It is, measured by the population-urbanization rate (*PUR*), which is in turn defined as the ratio of urban residents to the total population. Moreover, the land-urbanization rate (*LUR*) is defined as the ratio of the urban areas in reference to the total area, signifying the evolution of surface landscape from rural to urban land. Figure 3 shows the dynamic change of *LUR* and *PUR* over the last four decades. It was observed *PUR* kept rising at a relative stable speed from 25.7% in 1980 to 61.6% in 2010. After this, it gradually slowed down after 2010. Meanwhile, *LUR* exhibited a three-stage trend of “slight increase (1980–1990)—dramatic growth (1990–2010)—slow growth (2010–2017)”. The first stage was relatively stable with an increase from 1.4% in 1980 to 1.7% in 1990. During the aforementioned period, the reform of the household registration system loosened its strict control of population migration and thus allowed more rural inhabitants to move into cities and search for work. This is in turn lead to the increase of population-urbanization levels. During the 1990s, China gradually established the system regulating the Assignment of the Right to the Use of State-owned Land, which had a significant impact on China’s urban expansion. Since then, Zhejiang stepped into the stage of high-speed urban expansion along with the *LUR* rising from 1.7% in 1990 to 6.4% in 2010. After 2010, the increase of both *PUR* and *LUR* slowed down, signifying a shift from “extensive” to “intensive” urban expansion.

3.2 Spatial patterns of the urban areas from 1980 to 2017

The five selected metrics provide a general representation of the changes in the urban area landscape in Zhejiang from 1980 to 2017 (Table 2). An increase of *TA*, *NUMP*,

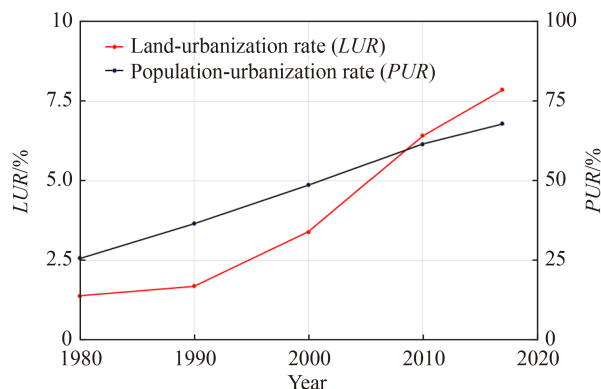


Fig. 3 Zhejiang’s land-urbanization rate and population-urbanization rate over the last four decades.

MPA, and *SHAPE_AM* indicate that the urban landscape became more dominant, large-grained, and irregular. Furthermore, *ENN_AM* exhibited a declining trend, signifying that the patches of urban areas became more concentrated over time.

The complex types of urban growth can be assigned to three categories, i.e., the infilling type, the edge-expansion type, and the outlying type. The spatial distribution and statistical value of the three newly urban growth categories for Zhejiang during the four periods are illustrated in Figs. 4 and 5, respectively. With respects to the patch area (*PA*), the edge-expansion type, accounting for more than 60%, was the most prevalent urban expansion growth category during the entire period. The proportion of *PA*, which was characterized by an infilling type of growth, was shown to be the least dominant, varying between 3% and 18%. Additionally, this category initially experienced a significant decline in the second period (1990–2000) and continuously grew during the two succeeding periods (2000–2010, 2010–2017). Furthermore, the percentage of the outlying type growth persistently dropped from 31% to 19% from 1980 to 2017. Among the patch number (*PN*) of the three urban growth categories, the edge-expansion type remained predominant during the entire period. The *PN* proportion of the outlying type reached its peak value of 24% during the period between 1990 and 2000 and then continuously decreased to a final minimum of 5%. Conversely, the *PN* proportion of the infilling type dropped to a nadir value of 21% during the period of 1990–2000, and then continuously rose to a maximum of 40% in the following periods. Since the outlying type of growth is more decentralized, and the infilling type is a more compact manner of urban expansion, we conclude that the urban areas grew in a scattered manner from 1990 to 2000. In the following two periods (2000–2010, 2010–2017), urban diffusion was gradually controlled, and urban areas grew compactly.

In addition, *AWMEI* values were calculated to illustrate the trend of landscape expansion. To be more specific, *AWMEI* were 24, 25, 29, and 36 in the four periods respectively, thus exhibiting a significant increasing trend. The most substantial increase in *AWMEI* was observed between the last two periods (2000–2010 and 2010–2017). Due to the fact that a larger value of *AWMEI* reflects a more compact manner of landscape expansion, it may be concluded that the urban growth of

Zhejiang is more condensed, especially in more recent periods.

3.3 Urban land input-output efficiency analysis in county-level

The present study used the 3-stage DEA model to measure the ULUE. As a result, we have managed to obtain the technical efficiency (TE), pure technical efficiency (PTE) and scale efficiency (SE) of Zhejiang's 63 county-level cities in 2017 (Fig. 6). The PTE reflects the technical level. Moreover, PTE of land use is measured by the efficiency of urban "intensive" land use. The SE illustrates the benefit level of a DMU from its scale enlargement, while the SE of land use is the benefit produced by unit input in the process of urban "extension" land use. The mean value for TE, PTE, and SE is 0.79, 0.83, and 0.95, respectively. The SE demonstrated a better performance than the PTE, indicating that the PTE mainly restricted the improvement of urban land use. Lower PTE is mainly due to extensive focus on the development of urban incremental space while ignoring the integration and optimization of urban stock space, therefore improving the technological innovation and management capabilities to enhance the reasonable utilization of land resources is crucial for Zhejiang at the present stage.

Spatially, the TE, PTE, and SE of urban land use of 63 county-level cities are quite different. The PTE showed a significant spatial aggregation distribution around Hangzhou, Ningbo, and South-west mountainous area, while SE was generally stable with a value fluctuation at around 0.9. The PTE and SE were further divided into low-efficiency (0.55–0.70], medium-efficiency (0.70–0.85], and high-efficiency (0.85–1.0], respectively. In general, 63 county-level cities of Zhejiang are distributed in 5 zones shown in Fig. 7 and the explanations about each zone are illustrated in Table 3. 22 cities including Hangzhou, Ningbo, Shaoxing, and cities with a relatively low level of development have high-efficiency PTE and SE, reflecting a relatively efficient urban land use. The PTE of 25 cities and 9 cities are at the medium-efficiency and the low-efficiency, respectively, where have the high-efficiency of SE, indicating that the resource allocation of these cities needs to be further optimized. Furthermore, 5 cities have medium-efficiency SE, with a high-efficiency PTE, indicating that they do not operate on the most appropriate scale. There are only 2 cities that have neither high-efficiency PTE nor SE, indicating that both the resource allocation and the scale need to be further improved.

4 Discussion

4.1 The future urbanization trend of Zhejiang Province

Henderson found every city to have an optimal scale from

Table 2 The five selected metrics of urban areas for Zhejiang from 1980 to 2017

Metrics	1980	1990	2000	2010	2017
<i>TA</i> /km ²	1410	1729	3458	6537	8004
<i>NP</i>	298	351	548	782	894
<i>MPA</i> /km ²	4.73	4.92	6.31	8.36	8.95
<i>SHAPE_AM</i>	2.61	2.66	3.50	3.48	3.55
<i>ENN_AM</i> /km	2.85	2.89	1.64	1.06	0.93

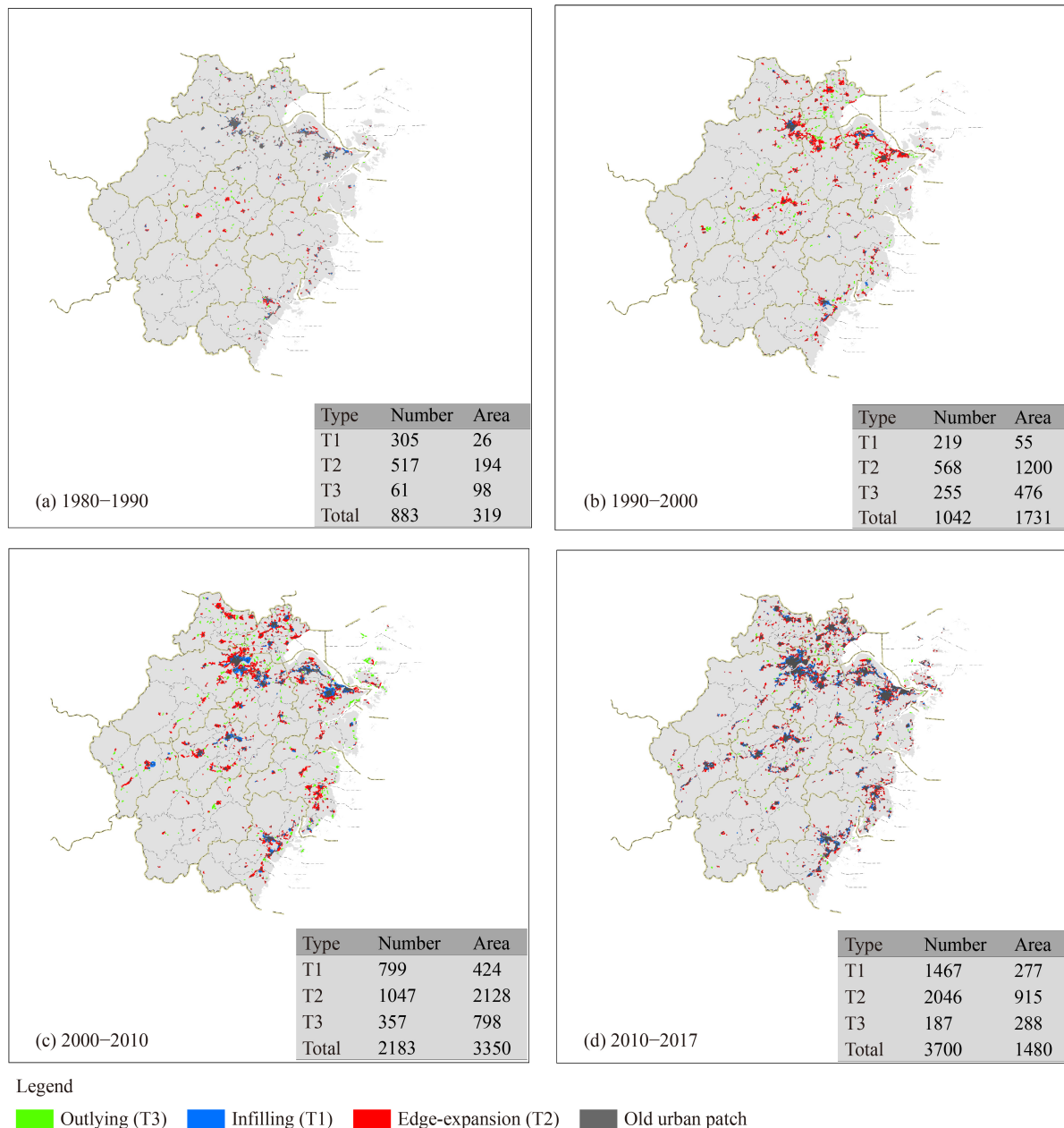


Fig. 4 Spatial distribution of the complex types of urban growth for Zhejiang in the four periods. (a) 1980–1990, (b) 1990–2000, (c) 2000–2010 and (d) 2010–2017.

the perspective of urban systems. That is, before reaching the optimal scale, the agglomeration effect is conducive to the growth of urban performance. Once it has exceeded the optimal scale, the crowding effect will appear and have a negative impact on urban performance (Henderson, 2003). Since the 2010s, the growth rate of urban areas in Zhejiang has slowed down significantly after a long-term dramatic urban expansion. Due to the increasingly strong constraints on ecological land, agricultural land and other resources on the growth of urban construction land, Zhejiang's urbanization conforms to the diminishing marginal effect of the input of construction land. In addition, according to the Northam theory (Northam,

1975), cities with an urbanization rate between 30% and 70% are in an accelerated development stage while those with a rate over 70% eventually enter a period of slow growth. The urbanization rate of Zhejiang has reached 70% in 2020, facing the challenge of both counter-urbanization and re-urbanization. Hence, the future growth rate of urban construction land will continue to "slow down", or even may demonstrate "negative speed".

In accordance with the analysis of urban land input-output efficiency, PTE was founding the primary factor restricting the improvement of urban land use. In other words, cities with lower PTE mainly focused on the development of urban incremental space while

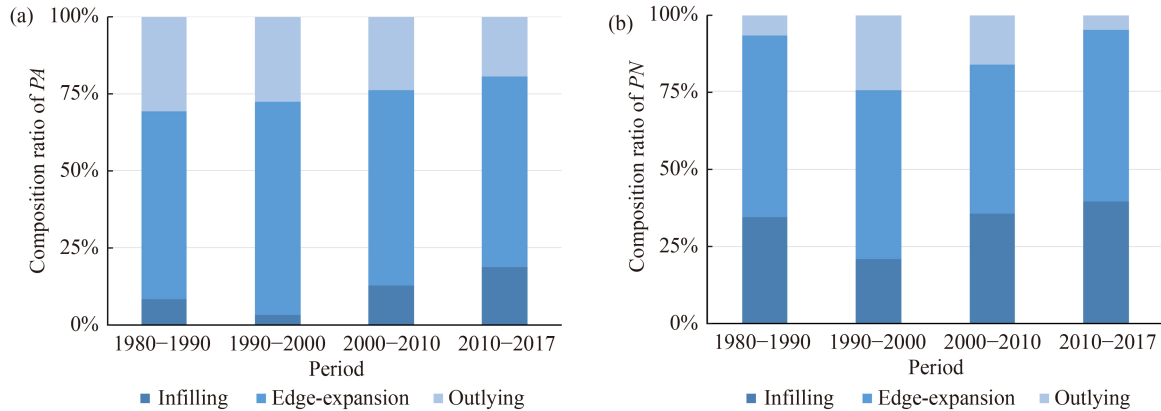


Fig. 5 Composition ratio of patch number (*PN*) and patch area (*PA*) for the complex types of urban growth during the four periods: (a) *PA* and (b) *PN*.

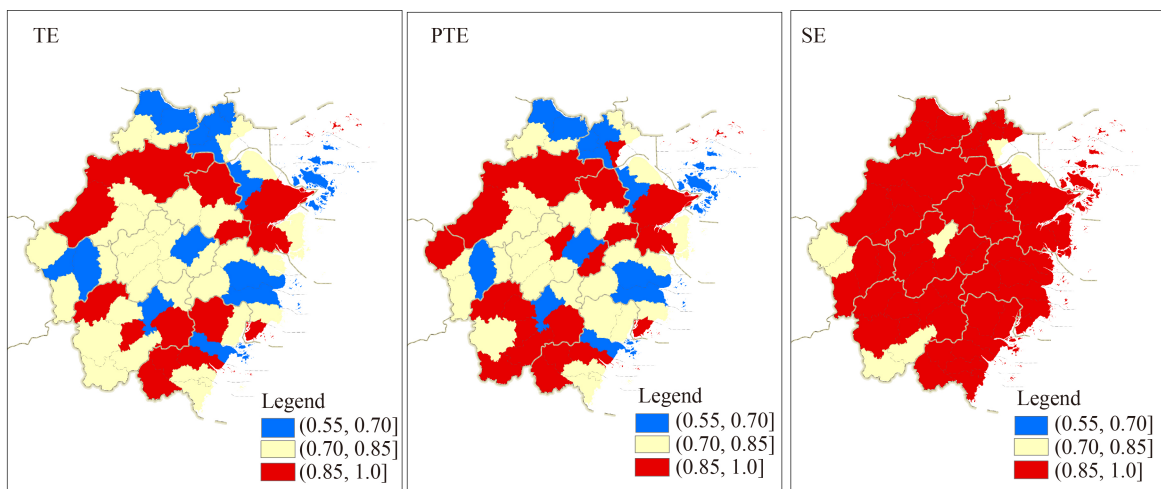


Fig. 6 Distribution of land input-output technical efficiency (*TE*), pure technical efficiency (*PTE*), and scale efficiency (*SE*) of Zhejiang's 63 county-level cities in 2017.

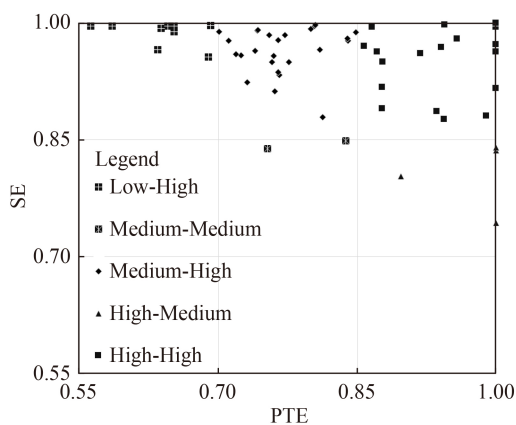


Fig. 7 The scatter diagram of land input-output pure technical efficiency (*PTE*) and scale efficiency (*SE*). (*PTE* and *SE* are divided into low-efficiency (0.55–0.70), medium-efficiency (0.70–0.85) and high-efficiency (0.85–1.0]. Correspondingly, 63 county level cities located in five zones).

disregarding the integration and optimization of urban stock space. Furthermore, excessive urban land inputs and insufficient resource allocation were the main reason

for the low levels of land use efficiency in these cities. The other two input factors, i.e., fixed asset investment and the number of employees in secondary and tertiary industries also demonstrated a certain degree of excess. Among the 63 county-level cities, 35 of them show redundancy of urban land with an average value of 10.0%, while 12 show redundancy of fixed investment with an average value of 7.0%, and another 12 have redundancy of labor with an average value of 8.1%, respectively (Fig. 8). The higher the value of urban land slack is, the more redundant the input of urban land will be. The top three cities with regard to the redundancy of urban areas are Cixi (32.7%), Jinhua (22.0%), and Wuyi (20.3%). Island cities such as Zhoushan and Daishan have excessive input of the total fixed asset investment because of the unique geographical and living environment. The labor of Wenling, Yongjia, Jinyun and Ruian appeared to be in surplus and to match their social-economic development. Therefore, it is concluded that the expansion of urban land should be constrained while increasing the input of capital and labor in the lower *PTE* areas to improve urban land use efficiency.

Table 3 Explanations for land input-output efficiency zones

Zones	Cities	Number	Explanation
High-High	Hangzhou, Ningbo, Shaoxing, Chunan, Jinyun, Longquan, Ninghai, Panan, Pujiang, Qintian, Ruian, Shensi, Songyang, Suichang, Taishun, Wencheng, Wuyi, Xinchang, Yongjia, Yongkang, Yuhuan, Yunhe	22/63	Both PTE and SE are the highest, reflecting these cities have relatively efficient urban land use
Medium-High	Jinhua, Zhoushan, Lishui, Anji, Cangnan, Deqing, Dongyang, Jiashan, Jiande, Jiangshan, Lanxi, Yueqing, Linhai, Longyou, Pinghu, Pingyang, Sanmen, Shenzhou, Tiantai, Tonglu, Tongxiang, Wenling, Xianju, Xiangshan, Zhuji	25/63	SE is the highest, indicating these cities operate on the most appropriate scale. However, the PTE is at the medium level, reflecting the resource allocation needs to be further optimized.
Low-High	Huzhou, Jiaxing, Quzhou, Taizhou, Wenzhou, Daishan, Haining, Yuyao, Changxin	9/63	PTE is the lowest while SE is the highest, indicating these cities have highly considered the development of urban incremental space while ignoring the integration and optimization of urban stock space.
High-Medium	Haiyan, Jingning, Kaihua, Qinyuan, Yiwu	5/63	PTE is at a high level, indicating these cities allocate reasonable resources into urban land use. However, SE is at a relative low level, illustrating that these cities do not operate on the most appropriate scale.
Medium-Medium	Cixi, Changshan	2/63	Both the PTE and SE need to be improved.

Furthermore, the relationship between GDP per capita and construction land per capita of Zhejiang’s 63 counties in 2017 was analyzed (Fig. 9). The 63 counties may be grouped into 3 zones according to their geographical characteristics, i.e., northern plain areas, southeast coastal areas and southwest mountainous areas. As a highly developed economic zone, the negative relationship in the northern plain zone indicates that the economic growth is relying on the supply of construction land less and less. In southeast coastal zone where there is a lack of land resources, the trend of increasing GDP per capita and growth of construction land per capita, indicates that the construction land supply plays a more significant role in improving economic development. In the southwest mountainous zone, the construction land supply can effectively advance the economic growth during the early stages. However, the supporting effect of construction land supply is gradually decreasing with continuous economic development. Based on the above analysis, we make a conjecture that the impact of construction land on economic growth is gradually decreasing with continuous urban expansion and economic development. When cities reach an advanced stage, economic growth should not rely on the continuous input of construction land. Rather,

it should focus on the technology and capital investment to improve land use efficiency.

4.2 Implications for territory spatial planning

Territorial spatial planning is an important approach to spatial governance, and high-quality spatial governance cannot be separated from the preliminary scientific research (Qiao et al., 2020). Zhejiang, which has a high level of social and economic development in China, has been under the rapid urbanization over the last four decades. Therefore, in accordance with the present situation and issues faced by Zhejiang’s urbanization, the present study provides the following valuable suggestions for the new round of TSP.

First, it is suggested that “Inventory Planning” should be the main direction of TSP. “Inventory Planning” is a relative concept to the traditional “Incremental Planning” which pays more attention to the newly-added construction land for supporting the needs of social and economic development. Many scholars have discussed the practices of the “Inventory Planning” (Jin et al., 2019; Huo and Guo, 2020; Li and Song, 2020). At present, the slower

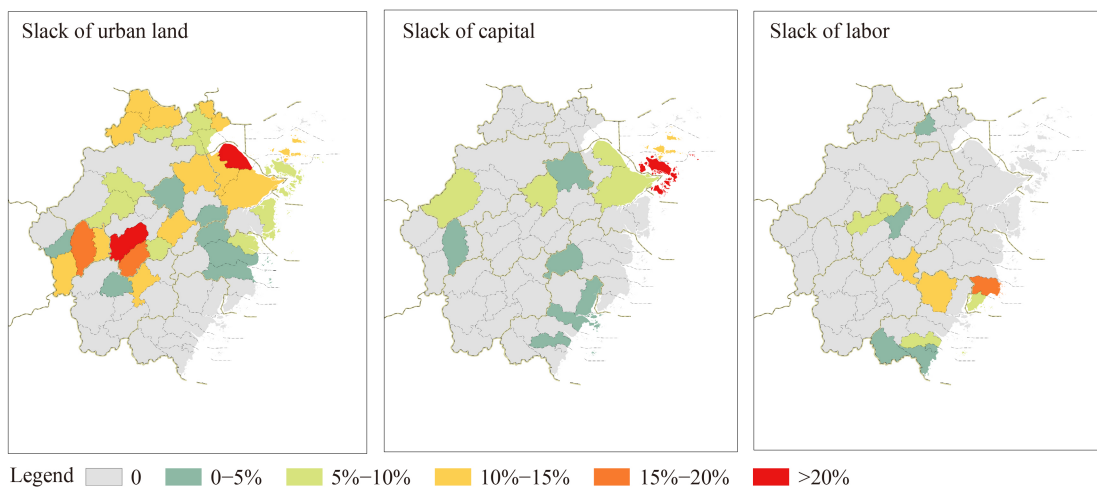


Fig. 8 Slack of urban land, capital and labor in 63 county-level cities.

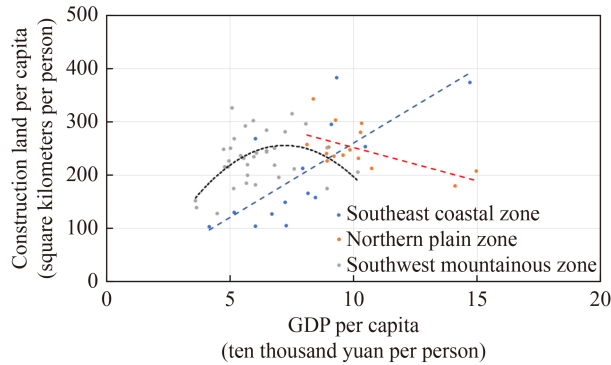


Fig. 9 The relationship between the urban areas per capita and GDP per capita.

and more compact urbanization trend in Zhejiang indicates that TSP is just in time to adjust its method to adapt the resource constraints and urgent need for the sustainable development. The urban construction should be centralized within the urban-town development boundary, as this would lead to a more compact manner of urban expansion. In addition, the construction land with low efficiency needs to be redeveloped to revitalize its potential value. Thus, a scientific policy should be explored for the allocation of newly-added construction land in accordance with the efficiency of existing construction land. For those with high land use efficiency of the existing construction land, the supply of newly-added construction land must be guaranteed to boost the economic development. For those with low land use efficiency of the existing construction land, the supply of new construction land should be limited to encourage the redevelopment of low efficiency land. Moreover, the requirements for the construction land, such as the entry threshold for investment and development intensity, should be gradually improved, and the planning of extensive land use with low output should be refused by strict orders.

Secondly, TSP should be more attentive to the protection of cultivated land and ecological resources in. Under the pressure of food security and the decrease in non-grain land, the protection of cultivated land of China is becoming more and more important. Moreover, rapid and disorderly urban expansions have seriously threatened and already destroyed the ecological environment, leading to a series of “urban diseases” and “negative externalities”. The new round of TSP has proposed three bottom lines, i.e., the red line of ecological protection (RLEP), which refers to the areas that have special and important ecological functions and must be strictly protected, permanent basic farmland (PBF), which is a special protection to ensure the supply of agricultural products and the urban-town development boundary (UTDB), which focus on urban construction to improve urban functions (Xinhua Agency, 2019b). Scientific delimitation of the three bottom lines will be the useful in forcing intensive and efficient land use.

Third, it is suggested that the economic growth should be guided away from simply relying on resources inputs and toward technology and capital investment. Through regional and long-term analysis, this paper has managed to put forward suggestions similar to other studies showing the impact of construction land on economic growth is gradually decreasing with continuous urban expansion and economic development (Zhong et al., 2010; Chen et al., 2016; Feng et al., 2018; Qiu et al., 2019). Therefore, different planning strategies should be provided according to different regions and stages. In the relatively undeveloped economic regions, more land resources are needed to boost economic development. Thus, the allocation of the newly-added construction land should be adapted in accordance with the population and capital investment. Economically developed regions should strive to transform to a different economic growth pattern through technology and capital investment. This would in turn, result in the promotion of land use efficiency and relieve the pressure on the environment. With respect to regions with excessive urban land, a policy of zero growth of built-up land should be implemented to initiate the transformation of economic development.

5 Conclusions

The present study analyzed the urban growth patterns for Zhejiang, a developed province in China, between 1980 and 2017 in an interval of 7–10 years. First, a novel approach combining the hexagonal mesh grid and multi-bandwidth kernel density estimation has been proposed to delimit urban areas from the distribution of artificial surfaces. Moreover, since the distribution of artificial surfaces can be easily and freely acquired from various land use and land cover production, our approach offers a universally applicable and convenient way to delimit the regional urban areas at a finer resolution. Furthermore, a total of 5 landscape-level metrics (*TA*, *NUMP*, *MPA*, *SHAPE_AM*, and *ENN_AM*) were chosen to evaluate the size, complexity, and isolation of the urban areas. As a result, the urban expansion exhibited a three-stage trend of “slight increase—dramatic growth—slow growth” over the last four decades. Urban landscape became more dominant, large-grained, concentrated, and irregular with time. Moreover, *LEI* was calculated in order to identify the growth types of a newly grown patch. This is in turn indicated that the newly urban patches grew in a relatively scattered manner between 1990 and 2000, and that the urban diffusion was gradually controlled beyond 2000. According to this trend, the growth rate of urban construction land will continue to “slow down” or even appear to have “negative speed” in the near future, and the urban morphology tends to be more compact in Zhejiang Province.

Furthermore, a 3-stage DEA model was applied to

calculate the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) of urban land use at the county level. The mean values for TE, PTE, and SE were 0.79, 0.83, and 0.95, respectively. SE demonstrated a better performance than PTE, indicating PTE as the main factor restricting the improvement of urban land use. The lower PTE was primarily the results of extensive focus being put on the development of urban incremental space while disregarding the integration and optimization of urban stock space. Thus, at the present stage, improving technological innovation and management capabilities to enhance reasonable utilization of land resources is crucial to Zhejiang.

With respect to the present situation and issues faced by Zhejiang's urbanization, the present study has put forth the following suggestions for the new round of TSP. First, it is suggested that "Inventory Planning" may be the main direction of TSP. At present, the urbanization tends to be slow and compact in Zhejiang. Therefore, TSP has sufficient time to adjust its methods and adapt to its resource constraints and urgent need for sustainable development. Secondly, TSP should be more attentive to the protection of cultivated land and ecological resources. Scientific delimitation of the three bottom lines (RLEP, PBF, and UTDB) may be the useful in forcing intensive and efficient land use. Lastly, TSP should guide economic growth away from relying on resources inputs toward technology and capital investment. With the continuous urban expansion and economic development, the impact of construction land on economic growth is gradually decreasing. Consequentially, different planning strategies should be provided in accordance with different regions and stages.

Data Availability

The data used to support this study are available from the corresponding author upon request.

Acknowledgement This work is supported by National Natural Science Foundation of China (Grant No.41901360).

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