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<https://doi.org/10.1057/s41599-025-05135-w>

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The spatiotemporal evolution and spatial effect of digitalization on urban land intensive use in the Yangtze River Economic Belt

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Land is essential for urban development. Increasing land use intensity can help with land shortage, and digitalization has become a new driving force for the development of society. This study uses panel data from 110 cities from 2011 to 2020 in the Yangtze River Economic Belt to empirically verify the impact of digitalization on urban land intensive use (ULIU). Based on analyzing the spatiotemporal evolution of urban digitalization and ULIU, the paper uses four spatial weight matrices and the spatial Durbin model to reveal the impact of urban digitalization on ULIU and discover spatial heterogeneity. We arrive at the following key conclusions: (1) Urban digitalization development is characterized by spatial heterogeneity; The pattern of development shifts from “multi-point” erratic distribution to “cluster” accumulation, and the degree of development in each city differs significantly. The Yangtze River’s downstream cities have become critical high-level digital agglomeration zones. (2) The difference in ULIU level between upstream and downstream of the Yangtze River Economic Belt is more prominent, and the dynamic transfer between tiers is relatively smooth. The correlation between neighboring cities is significant, and the urban spatial agglomeration feature is noticeable (the High-High areas are mainly concentrated in Shanghai, Jiangsu, and Zhejiang). (3) Digitalization can significantly improve ULIU. The adjacency and geospatial effects are pronounced. Spatial heterogeneity is prominent, and cities in the eastern region and within urban agglomerations are subject to a more vital role of digitalization in enhancing ULIU. Finally, based on the findings, this paper proposes to boost ULIU in the Yangtze River Economic Belt.

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Introduction

The land is the spatial carrier of human production and living activities, as well as a factor of production. However, the imbalance between economic subjects and urban land use has accelerated with the rapid development of the economy and society and the further expansion of the urbanization scale (Wu et al., 2014). The “Several Opinions of the Central Committee of the Communist Party of China and the State Council on Establishing a National Land Spatial Planning System and Supervising its Implementation” issued in 2019 clearly stated that it is essential to define geographical borders such as permanently barren farmland, ecological red lines, and urban development boundaries. Bottom-line limits should be tightened to make room for China’s long-term development. Local governments are now obligated to promote the potential of livestock land and ensure the optimal and intensive use of urban construction land. The urban development border is crucial in limiting the haphazard spread of urban construction land (Deng et al., 2025). Therefore, using land efficiently and intensively has become an important issue (Ma et al., 2024). The Chinese government has long placed a premium on intensive land utilization. It has implemented several associated rules and regulations for intensive and effective land use and sustainable urban development (Luo et al., 2021). With the development of informatization, the digital economy has become an indispensable and essential part of China’s urban economic development today, and the trend of digital products is unstoppable (Christmann and Schinagl, 2023). With the advancement of digitalization, whether it can help improve the efficiency of urban land utilization is an unavoidable issue that needs to be resolved promptly.

Research on urban land intensive use (ULIU) has always been a hot issue in academic circles (Dong and Huang, 2025). Existing research mainly focuses on four aspects: (1) ULIU evaluation indicators and selection of calculation methods. Most researchers conduct thorough assessments based on economic, social, ecological, and other issues (Jing et al., 2020; Xue et al., 2022) when choosing ULIU evaluation indicators based on intensive land use and the perspective of sustainable green development. Some academics have adopted a multi-factor evaluation approach regarding land input level, usage intensity, efficiency, and structure (Luo et al., 2022; Ma et al., 2024). In terms of measurement methods, there are mainly comprehensive methods such as the entropy weight method (Luo et al., 2022), analytic hierarchy process (Dong et al., 2017), principal component analysis method (Xu et al., 2021), and other methods from the perspective of efficiency, such as the stochastic frontier model (Dong et al., 2017), the data envelopment analysis method (Zhang et al., 2016) and so on. In addition, some scholars have introduced methods like system dynamics and material element analysis to measure land intensive use (Xiong et al., 2019). A model for assessing the possibility of land intensive usage based on technical efficiency measurement was also put forth by Wang et al. (2019) (Wang et al., 2019) at the same time. In addition, with the application and development of AI technology in geospatial, the application of geospatial artificial intelligence (Geo AI) models has become critically important in spatial geography (Hsu and Li, 2023). It will also be a noteworthy measurement method in the future. The selection of indicators and methods has greatly enriched and improved the ULIU index evaluation system. On the premise of diversification of quantitative analysis indicators and strategies, evaluation has been carried out in national (Yang et al., 2015), urban agglomerations (Feng et al., 2023; Zhang et al., 2023b), provincial (Meng et al., 2023), micro-city (Fan et al., 2023a; Ma et al., 2024; Zhang et al., 2023d), and industrial park scales (Ye et al., 2023) in existing empirical studies. (2) Interrelationships between ULIU and other urban systems. Based on the theory of

system, there has been research on ULIU and urban scale [20], new urbanization (Zhang et al., 2023e), economic and social development (Jing et al., 2020; Zhang et al., 2022a), industrial structure (Lan et al., 2023; Ye et al., 2023), carbon emissions (Yang et al., 2023b; Zhang et al., 2023a), ecological security (Zhang et al., 2023c), national level and local levels (Zhang et al., 2025), etc. Their relationship has been demonstrated, and many valuable conclusions have been drawn. The development of ULIU also significantly improves mobility (Appleyard et al., 2023), air pollution emissions (Dias et al., 2022), urban land growth (Lukas et al., 2023), and carbon emission efficiency (Zhang et al., 2016). (3) Existing research has shown that a variety of elements, including society, economy, nature, policy, economic development level, industrial structure level, scale and structure of the urban system, urbanization level, populations (Huang et al., 2024), land prices (Qi et al., 2025), and highway network, have an impact on ULIU (Chen et al., 2023; Huang et al., 2024; Qi et al., 2025; Zhang et al., 2022b; Zhang et al., 2022c). Many factors affect ULIU, and valuable conclusions have been drawn from their respective perspectives, providing a basis for subsequent research. However, in China, which is entering a new era, the vigorous development of the digital economy is affecting all aspects of the economy and society, and the impact of digitalization on ULIU is still a blank that needs further clarification. (4) The study of the spatial spillover of land intensive usage has steadily drawn attention from the academic community due to the maturity and widespread application of spatial measurement methodologies (Luo et al., 2022). Studies show China’s land intensive use considerably affects proximity radiation and spatial dependence (Peng et al., 2022). Therefore, future research should focus on the spatial characteristics of land intensive use. There has been much discussion about the idea and significance of ULIU, its evaluation techniques, motivating factors, and interactions with other urban systems. However, most studies examine land intensive use from the standpoint of input intensity and economic efficiency, mainly ignoring the use of land for economic and ecological purposes and the social advantages of such usage (Luo et al., 2022). Therefore, the high-quality, sustainable content and index of ULIU need to be further supplemented and improved.

The study of digitalization is becoming more in-depth as it permeates every business sector and society. Currently, it is primarily seen in three areas: the evaluation of digitalization (Jovanović et al., 2018), which includes the choice of indicators, etc. Some scholars measure the level of regional digitalization directly or concerning all or part of the indicators of the digital economy (Gu et al., 2022; Habibi and Zabardast, 2020). Other scholars now use various institutions’ indexes of the digital economy (Haruna and Alhassan, 2022). According to the existing literature, it is reasonable to select digitalization indicators according to the relevant indicators of the digital economy combined with the research topic (Ma et al., 2023c; Wang and Xu, 2023). Therefore, this study will also refer to the general digital hands and some particularities of land resources for selection. The second is the relationship between digitalization and various facets of socio-economic growth (Fan and Wu, 2021; Haruna and Alhassan, 2022; Ma et al., 2023c; Salykov et al., 2023), such as the interactions between digitalization and high-quality development at the provincial level in China (Fan and Wu, 2021); Ma et al. (Ma et al., 2023c) explore the role of digitalization in promoting green and sustainable urban development. In addition, digitalization has also been studied to promote enterprise development (Salykov et al., 2023) and other social aspects, such as women’s entrepreneurial ability (Wang et al., 2023c), which are beneficial to enterprise development and social progress. The third is how digitalization affects the environment. It includes whether it can

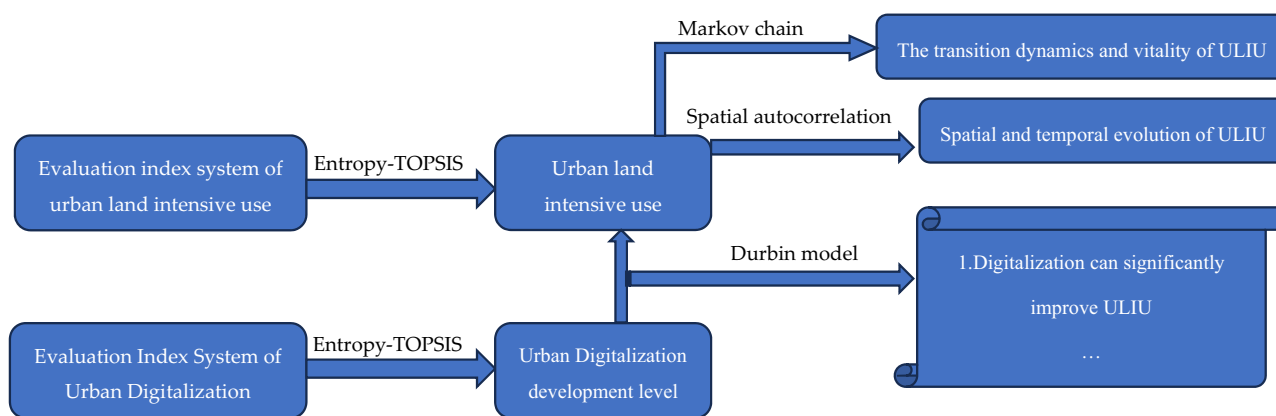


Fig. 1 Frame structure.

raise habitat quality (Pang et al., 2021) and the inverted U-shaped relationship between digitalization and environmental performance (Ahmadova et al., 2022). In addition, International scholars mainly study the benefits of developed and underdeveloped regions from the information age by taking countries as units (Vu and Asongu, 2020). There are few studies on the effects of digitalization on various nations' areas, though (Liu et al., 2021). However, from the research perspective of digitalization transformation, it can also be seen that the research on the relationship between digitalization and the ULIU still needs to be more involved and needs further exploration and research.

From the previous literature research, there are mainly areas for improvement in the following aspects. (1) There is room for improvement in evaluating urban land-intensive use. A more effective approach would involve a multi-index evaluation, comparing the results to the best and worst outcomes. While entropy weight theory can assist in determining data proportion, it has some limitations that must be considered. (2) There are still some gaps in the research on the factors influencing ULIU, especially the influence of digitalization. In the context that digitalization affects all aspects of economic and social development, it is necessary to improve the exploration of whether it has an impact on ULIU and how it develops. (3) The research on the spatial effect of ULIU needs to be improved. Previous studies have proved the existence of adjacency spatial spillover effect in ULIU, but its spatio-temporal evolution and other spatial effects need to be explored. (4) There are only a few micro-level studies on ULIU. From an international perspective, research tends to focus on the country as a whole, whereas, within China, discussions are primarily framed at the national level with a provincial focus. Therefore, conducting more in-depth micro-level studies at the city and regional levels is essential to provide a more realistic and nuanced understanding.

The level of ULIU is closely related to sustainable development and people's livelihood in the future. Therefore, the in-depth study of ULIU is critical in both academic theory and practical guidance. This work employs the spatial Durbin model and other metrology approaches to empirically examine the influence of digitalization on ULIU and further tests the impact of spatial heterogeneity on ULIU based on the panel data of 110 cities from 2011 to 2020 in the Yangtze River Economic Belt. This study needs to make up for the shortcomings of existing research. Our work makes the following contributions to the existing literature. Firstly, in terms of the general method of evaluating ULIU, we combine the available Entropy weight method with the technique for order preference by similarity to an ideal solution (TOPSIS method) and adopt the Entropy-TOPSIS method, which can make good use of the advantages of the two ways to make the

evaluation results of ULIU more scientific and reasonable. Secondly, it explores the impact of digitalization on ULIU. This not only fills the research on the influencing factors of ULIU but also enriches the research on the theory and practice of digitalization. Thirdly, the work improves the ULIU spatial effect. The result analyses the spatio-temporal evolution of ULIU and explores its spatial development with the four spatial weight matrices. Finally, innovation has also been made in the selection of indicators of variables and the mic-sample. The structure flow chart of the whole article is shown in Fig. 1. In conclusion. This study aims to explore the influencing mechanism and spatial effects of digitalization on urban land intensive use from the perspective of spatial economic geography through rigorous empirical research to provide a reference for improving urban land intensive use and promoting high-quality, sustainable development in cities.

Research design

Overview of the study area. The Yangtze River Economic Belt spans 11 provinces and municipalities in East, Central, and West China, encompassing Zhejiang, Anhui, Shanghai, Hubei, Jiangsu, Hunan, Sichuan, Chongqing, Jiangxi, Guizhou, and Yunnan (refer to Fig. 2). It traverses three major geographical regions of China, covering approximately 2.05 million km², which is about 21.27% of the nation's total land area. The belt is home to roughly 40% of China's population, with an urbanization rate exceeding 60% and contributing over 45% to the national GDP, making it one of China's most dynamic and strategically significant areas. Due to substantial regional disparities in socio-economic development and natural resources, the belt is divided into the upper, middle, and lower reaches. The upper reaches include 33 cities, such as Guizhou, Yunnan, Chongqing, and Sichuan; the middle reaches comprise 36 cities, including Hunan, Hubei, and Jiangxi; and the lower reaches encompass 41 cities, such as Anhui, Zhejiang, Jiangsu, and Shanghai. The Yangtze River Economic Belt, which features urban agglomerations like the Yangtze River Delta, Chengdu-Chongqing, and the Midstream urban areas, is highlighted in China's 13th Five-Year Plan as a critical regional development strategy and is poised to become a globally influential demonstration of ecological civilization. As a rapidly urbanizing region and one of the most environmentally stressed basins (Yuan et al., 2022), the belt faces escalating tensions between environmental conservation, urban development, and agricultural land protection. The conversion of substantial arable and ecological land to construction land, especially when coupled with inefficient urban land use, poses significant challenges to sustainable development (Ma et al., 2023b). Guided by the

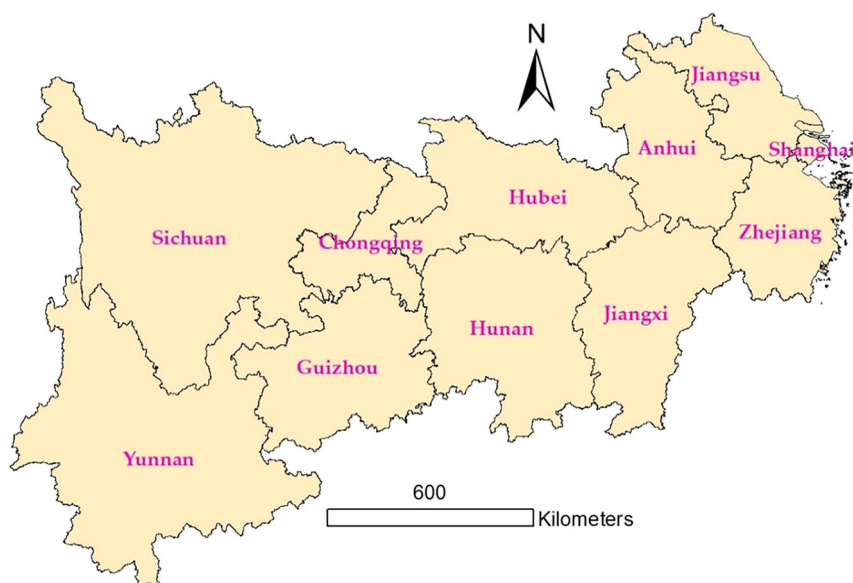


Fig. 2 General View of the Yangtze River Economic Belt.

principle of “prioritizing protection over development,” the focus is on sustainable economic and social growth with intensified land use efficiency. This study examines the impact of digitalization on urban land use intensity and its spatial effects within the Yangtze River Economic Belt, aiming to provide scientific support for sustainable regional development and optimal land use.

The base map for the map is from Natural Earth (<http://www.naturalearthdata.com/>).

Data sources. From 2011 to 2020, this paper selects 110 cities in the Yangtze River Economic Belt, given sample continuity and data accessibility. The relevant data involved are achieved from the China Statistical Yearbook of Cities, China Statistical Yearbook of Land and Resources, China Statistical Yearbook of Regional Economy, China Environmental Statistical Yearbook, China Statistical Yearbook, China Statistical Yearbook of Industrial Economy, China Statistical Yearbook of Electronic Information Industry, China Statistical Yearbook of Basic Units, “China Statistical Report on Internet Development Status,” “China Statistical Yearbook of Civil Affairs,” as well as the statistical yearbooks of provinces, cities and autonomous regions, and the statistical bulletins of social development as a supplement. This paper replaced individual outliers and missing data with mean values from neighboring years or provinces. The Resource and Environment Science and Data Center (www.resdc.cn) provided the map (accessed on 1 August 2022).

Construction of evaluation indicator system

Evaluation index system of urban digitalization. The measuring indicators need to be more consistent, and research on urban digital development needs to be expanded. Based on existing studies, the construction of regional digitalization evaluation systems can be broadly categorized into three types: first, the univariate index is employed based on the rate of Internet penetration and the average number of people who utilize broadband Internet access (Habibi and Zabardast, 2020); second, some studies borrow the indicators of the digital economy (Jovanović et al., 2018), including the European Union (EU) Digital Economy and Society Index (DESI) and Organization for Economic Cooperation and Development (OECD) (Jovanović

et al., 2018); third, when it comes to the digital economy and informatization evaluation indicators, some studies use hands based on their research objectives, and several index systems are built from various viewpoints (Fan and Wu, 2021). A single indicator cannot wholly and accurately depict regional digital growth since digitalization is a complex system that propels economic, social, and ecological progress (Pang et al., 2021). This research thoroughly assesses four dimensions of the existing literature (Liu et al., 2021): digital application, digital industrial development, digital infrastructure, and digital financial inclusion. Digital infrastructure is the regional digitalization’s hardware. The essential manifestation of digital connotation is a digital application, which reflects the degree of integration between digitalization and regional economy and society. Digital industry development is required to support the innovation of digital products (Pang et al., 2021). Incorporating the true meaning of digital financial inclusion, digital finance can serve the needs of small, medium, and micro businesses and low-income groups who typically find it difficult to access financial services (Guo et al., 2020). The capacity of mobile phone exchanges per 100 people, the density of long-distance cable, and the number of Internet broadband access ports per 100 people are used to assess the development status of digital infrastructure. The ratio of digital industry employees to employees in urban units, the share of digital industry income in regional GDP, and the percentage of digital industry fixed asset investment in total fixed asset investment in society are all indicators of digital industrial development. The penetration rate of mobile phones, the number of websites owned by businesses, and the volume of express business per capita demonstrate digital applications in production and life. Digital Financial Inclusion adopts the Peking University Digital Financial Inclusion Index (Guo et al., 2020) from three dimensions: digitalization degree, coverage breadth, and use depth. The final urban digital evaluation system is shown in Table 1. On this basis, the Entropy-TOPSIS model is used to measure the digitalization level level of each city.

^aThe number of employees in the digital industry is replaced by the number of employees in the information transmission, software and electronic technology services; The investment in fixed assets of digital industry is reflected by the investment in fixed assets of computer services, information transmission and software industry. Software revenues express digital revenues.

Table 1 Evaluation Index System of Urban Digitalization.				
Object	Dimension	Index (Attribute)	Indicator description (Unit)	Weight
Urban digitalization level	Digital infrastructure	The density of long-distance cable (+)	Cable length per square kilometer (km)	0.064
		Mobile Internet Basics (+)	Mobile telephone exchange capacity per 100 people (households)	0.047
	Digital application level	Broadband Internet Basics (+)	Number of Internet broadband ports per 100 people (units)	0.057
		Mobile phone penetration (+)	Number of mobile phones per 100 households (units)	0.024
		Number of websites owned by enterprises (+)	Number of websites per 100 enterprises (units)	0.011
		Express business volume per capita (+)	Express business volume per capita (pieces)	0.253
	Digital industry development	Digital industry personnel scale (+)	The proportion of employed persons in the digital industry to employed persons in urban units (%) (Pang et al., 2021)	0.101
		Digital industry investment intensity (+)	The percentage of fixed asset investment in the digital industry compared to overall fixed asset investment in society (%)	0.169
		The economic scale of the digital industry (+)	The share of revenue generated by the digital industry in regional GDPa (%)	0.175
		The breadth of coverage (+)	Digital Financial Inclusion Coverage Index	0.037
Digital Financial Inclusion	Digital Financial Inclusion	Depth of use (+)	Digital Financial Inclusion Penetration Index	0.034
		Digital degree (+)	Digital Financial Inclusion Digitalization Index	0.029

Evaluation index system of urban land intensive use. The construction of intensive, green, and efficient land space is the primary premise for the high-quality development and building of “beautiful China” in the new era (Yang et al., 2020). The land is crucial to urban economic and social activities. Therefore, land intensive users’ social and ecological benefits should be fully considered when establishing an indicator system to assess urban land intensive use (Luo et al., 2020). Scholars have defined and measured land use efficiency and output benefits from different dimensions based on the actual development status of various regions, changing the input combination and management mode of land based on the existing land stock (Yang et al., 2020). Scholars have recently constructed index systems for evaluating urban land intensive use from land input level, land use intensity, land use structure, and land output benefit (Xu et al., 2021). Based on the existing research results (Jing et al., 2020; Wan and Chen, 2018; Weng and Zhang, 2022; Xu et al., 2021; Yang et al., 2020; Zhang et al., 2016; Zhao and Hu, 2016), this paper incorporates land-intensive users’ social and ecological benefits into the assessment index system to make it more suitable for high-quality, sustainable urban development. To this end, the evaluation index system of urban land intensive use constructed in this study consists of six indicators: (1) land input. Urban growth depends on land, and how much land is invested has a significant impact on how effectively it is used (Ma et al., 2023a); it carries out multiple composite functions such as economy, society, population, and nature (Wang et al., 2022) and covers eight types of land, including residential and industrial land. Based on the above analysis, this work selects three sub-indicators for representation (see Table 2). (2) land utilization intensity. It shows the recent status and development potential of land intensive use, especially the population density, illustrating the degree of future ULIU (Yang et al., 2023a). Therefore, we selected three representative indicators as the basis for measurement (see Table 2). (3) Land use structure. This shows that the region’s current economic and social development situation brings about the existing land use status [56] and reflects the land environment’s green level (Wang et al., 2023d). (4) Economic benefits of land. It is mainly the economic effect per unit of land, which includes the economic creation effect, consumption level, and fiscal capacity. (5) Social Benefits of Land. It is mainly the social effect of land. (6) Ecological Benefits of Land. Society has paid more and more attention to the ecological efficiency of land, which is related to the sustainable development of ecology (Dong et al., 2017; Orlov et al., 2023). On this basis, three sub-indicators are selected to reflect each level, ensuring each indicator meets its scientific and rational nature (see Table 2 for details). The evaluation method selection is based on the impact of the critical information brought by the change of the indicator system to the intensive land use rather than the input-output efficiency perspective based on the equality of all indicator items because the significant change of the indicator system better reflects the reliability and scientific of the land intensive use. Therefore, this paper chooses the Entropy-TOPSIS comprehensive evaluation method to measure land intensive usage in each city.

Research methodology

Entropy-TOPSIS model. Traditional measurement methods possess unique characteristics, yet using multiple indicators has emerged as the dominant approach. Indicator weights are typically assigned within this framework using the entropy weighting method. This method ascertains the weight of each indicator based on the information content reflected in the variability of the data, thereby minimizing the influence of subjective bias in the weighting process. The Technique for Order Preference by

Table 2 Evaluation index system of urban land intensive use.				
Object	Dimension	Index (Attribute)	Indicator description (Unit)	Weight
Level of urban land intensive use	Land input	Average fixed asset investment by land (+)	Fixed asset investment / total construction land area (10,000 yuan/km ²)	0.071
		Average real estate investment completion by land (+)	Real estate investment expenditure / total construction land area (10,000 yuan/km ²)	0.109
Land use intensity	Land use intensity	Number of employees in secondary and tertiary industries on average by land (+)	Number of people employed in secondary and tertiary sectors / total construction land area (people/km ²)	0.089
		Urban construction land per capita (+)	Total construction land area/household population (m ² /person)	0.101
Land use structure	Land use structure	Population density (+)	Household population / total construction land area (people/km ²)	0.038
		Urban residential land per capita (+)	Urban residential land area/household population (m ² /person)	0.100
Economic benefits of land	Economic benefits of land	The proportion of land for public facilities (+)	Public facility land area / total construction land area (%)	0.066
		The proportion of industrial land (+)	Industrial land area / total construction land area (%)	0.020
Social Benefits of Land	Social Benefits of Land	The proportion of green space (+)	Green space area / total construction land area (%)	0.048
		GDP per land (+)	GDP / total construction land area (10,000 yuan/km ²)	0.052
Ecological Benefits of Land	Ecological Benefits of Land	Land-average fiscal revenue (+)	Government revenue / total construction land area (10,000 yuan/km ²)	0.048
		Total land-average retail sales of consumer goods (+)	Total retail sales of social consumer goods / total construction land area (10,000 yuan/km ²)	0.060
Land use intensity	Land use intensity	Total local average postal and telecommunications services by land (+)	Total postal and telecommunications business / total construction land area (10,000 yuan/km ²)	0.032
		Total land-average water supply (+)	Total urban water supply / complete construction land area (10,000 t/km ²)	0.073
Land use structure	Land use structure	Urban road area per capita (+)	Road area/household population (m ² /person)	0.065
		Greening coverage of urban built-up areas (+)	Greening area / built-up area (%)	0.007
Ecological Benefits of Land	Ecological Benefits of Land	Land-average industrial SO2 emissions (-)	Industrial SO ₂ Emissions / total construction land area (t/km ²)	0.014
		Land-average industrial soot emissions (-)	Industrial soot emissions / total construction land area (t/km ²)	0.007

Similarity to Ideal Solution (TOPSIS) facilitates quantitative ranking by comparing the relative distances between each object of evaluation and both the ideal and anti-ideal solutions, offering the benefits of simplicity and rationality in its outcomes. The Entropy-TOPSIS method leverages the strengths of both the entropy weighting (see Tables 1 and 2) and TOPSIS methods, enhancing the objectivity and rationality of the measurement results (Huang et al., 2018). Extant literature (Wang et al., 2021b; Yi et al., 2021; Yuan, Liu, et al., 2023) indicates that this integrated approach is extensively employed in comprehensive evaluations due to its straightforward computation and favorable outcomes. Given the compatibility of the evaluation indexes with this methodology, we opt to utilize the Entropy-TOPSIS method to assess the levels of urban digitization and intensive land use. The detailed calculation process is outlined below.

Assuming that there are n cities, the evaluation of urban digitalisation and urban land intensive utilisation each has p evaluation indicators, forming the original indicator data matrix:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \quad (1)$$

where x_{ij} denotes the value of the j th evaluation indicator for the i th city.

(1) Finding the ratio

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (2)$$

(2) Finding entropy

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}, e_j \in [0, 1] \quad (3)$$

(3) Information redundancy value

$$d_j = 1 - e_j \quad (4)$$

(4) Weighting

$$w_j = -\frac{d_j}{\sum_{j=1}^p d_j} \quad (5)$$

(5) Weighting normalization

$$z_{ij} = -\frac{x_{ij}}{\sqrt{\sum_{i=1}^n x_{ij}^2}} \quad (6)$$

(6) Construct weighting matrix

$$z_{ij}^* = z_{ij} \cdot w_j \quad (7)$$

Obtain a weighting matrix

$$Z^* = \begin{bmatrix} z_{11} \cdot w_1 & z_{12} \cdot w_2 & \cdots & z_{1p} \cdot w_p \\ z_{21} \cdot w_1 & z_{22} \cdot w_2 & \cdots & z_{2p} \cdot w_p \\ \vdots & \vdots & \ddots & \vdots \\ z_{n1} \cdot w_1 & z_{n2} \cdot w_2 & \cdots & z_{np} \cdot w_p \end{bmatrix} \quad (8)$$

(7) Find the best and worst values

$$\begin{cases} z_{ij}^{*+} = \max(z_{1j}^{*+}, z_{2j}^{*+}, \dots, z_{pj}^{*+}) \\ z_{ij}^{*-} = \min(z_{1j}^{*-}, z_{2j}^{*-}, \dots, z_{pj}^{*-}) \end{cases} \quad (9)$$

(8) Optimal and worst distances

$$D_i^+ = \sqrt{\sum_j (z_{ij}^* - z_{j}^{*+})^2} \quad (10)$$

Table 3 Markov transition probability matrix ($k = 4$).

t_i/t_{i+1}	E	L	M	I
E	P_{EE}	P_{EL}	P_{EM}	P_{EI}
L	P_{LE}	P_{LL}	P_{LM}	P_{LI}
M	P_{ME}	P_{ML}	P_{MM}	P_{MI}
I	P_{IE}	P_{IL}	P_{IM}	P_{II}

E is Extensive utilisation, L is Low utilisation, M is Moderate utilisation, I is Intensive utilization.

$$D_i^- = \sqrt{\sum_j (z_{ij}^* - z_{j}^{*-})^2} \quad (11)$$

(9) Relative structural proximity

$$C_i = -\frac{D_i^-}{D_i^+ + D_i^-} \quad (12)$$

The ranking is based on the value of C_i . The larger C_i is, the closer the evaluation object is to the optimal value.

The Markov chains approach (MCs). According to (Agovino et al., 2019), a Markov chain is a Markov process with discrete time and state. The technique approximates the entire process of regional evolution by first discretizing the degree of intense urban land use into k types, then calculating the probability distribution of the associated classes and their interannual fluctuation. Therefore, to seek the law of development inherent in the intensive use of land, we use the Markov chains approach to explore it. Generally, the transfer between urban land intensive use types in different years can be expressed as a $k \times k$ Markov transition probability matrix (see Table 3). The probability distribution of all urban land intensive use level types in year t is described as a $1 \times k$ state probability vector P_t , denoted as $P_t = [P_{1,t}, P_{2,t}, \dots, P_{k,t}]$. The one-step transition likelihood that an area belonging to type i in year t will be transferred to type j in the following year is represented by the element P_{ij} in Table 3 and is calculated using the equation as follows:

$$p_{ij} = \frac{n_{ij}}{n_i} \quad (13)$$

Where n_{ij} stands for the total number of type i areas from year t that were changed to type j in year $t + 1$ during the whole study period, and n_i represents the total number of type i areas from all years.

The type transfer is smooth if a city's land intensive use level is i in the first year and stays that way in the following year; if the type of urban land intensive usage level advanced, it is referred to as an upward transfer; otherwise, the urban land intensive usage level transfers downward.

Spatial autocorrelation analysis. To ascertain whether neighboring cities influence the intensive use of land and to verify its spatial correlation, a spatial autocorrelation test is conducted. In this study, the global Moran's I index, introduced by Patrick Alfred Pierce Moran in 1950, is employed for spatial autocorrelation analysis of urban land intensive use levels. The correlation is calculated using the following formula (He et al., 2023):

$$\text{Moran's } I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} |x_i - \bar{x}| |x_j - \bar{x}|}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} |x_j - \bar{x}|} \quad (14)$$

The value range of I in the formula is $[-1, 1]$. When I is greater than 0, it indicates that the distribution of urban land intensive use levels has a positive spatial correlation; the higher the value, the stronger the spatial correlation; conversely, when I is less than

Table 4 Variable description.			
Variable	Surrogate letters	Measurement methods	Researches
Land Intensive Use	land	The measured value of urban land intensive utilisation level obtained by calculation	Lu et al.(2022) (Lu et al., 2022) Luo et al. (2022) (Luo et al., 2022) Hu et al. (2021) (Hu et al., 2021)
Digitalization level	dig	The measured value of urban digitalization development level	
Urban innovation level	il	patent applications per capita (piece/ten thousand people)	
Urbanisation rate	urb	The percentage of permanent residents in the total population at the end of the year (%).	Zhuo et al. (2022) (Zhuo et al., 2022)
Environmental regulation	erp	SO ₂ removal rate (%)	Lu et al. (2022) (Lu et al., 2022) Yang et al. (2023a; 2023b; 2023c) (Yang and Wang, 2022)
Economic Development Level	pgdp	The GDP index was converted to real GDP using 2010 as the base period, which was then divided by the total population of each city to get the real GDP per capita.	Luo et al. (2022) (Luo et al., 2022) Chen et al. (2023) (Chen et al., 2023)
Industrial Structure	ind	The percentage of the output value of the tertiary industry in GDP	Wang et al. (2023a; 2023b; 2023c; 2023d) (Wang et al. 2023b)

0, it indicates that the distribution of urban land intensive use levels has a negative spatial correlation; when I is equal to 0 means that the urban land intensive use level distribution does not have a spatial correlation. x_i, x_j denote the level of urban land intensive use in the i th and j th cities in China, respectively, \bar{x} is the average value, and n is the total number of study units (Hao and Liu, 2016).

To further explore the spatial autocorrelation of elements within a local area and its significance, the LISA index I_i was introduced to reflect the spatially correlated distribution characteristics of the intensive urban land utilization level (Zhang and Bi, 2020), calculated as follows:

$$I_i = \frac{n(X_i - \bar{X}) \sum_{j=1}^n W_{ij}(X_j - \bar{X})}{\sum_{i=1}^n (X_i - \bar{X})^2} \tag{15}$$

Spatial econometric model. (1) Model setting. Following available research on intensive urban land use (Tan et al. 2022; Wang et al. 2021a; Yang et al. 2022; Zhao et al. 2022), the level of intensive urban land utilization is selected as the dependent variable in this study. To produce more accurate results, the independent variables are chosen beside the primary explanatory variable, urban digitalization, namely, the urbanization rate, economic development level, industrial structure, and urban environmental regulation level of cities. Since there is a spatial correlation among cities regarding intensive land use, it may produce bias in coefficient estimation if this spatial correlation is ignored when investigating the influencing factors. As a result, a spatial econometric model must be developed. The spatial Durbin model used in this investigation was created as follows:

$$Land_{it} = p \sum_j^n W_{ij} Land_{it} + \alpha_0 + \beta_0 X_{it} + \sum_{j=1}^n W_{ij} (X_{it}) \gamma_1 + \mu_i + \lambda_t + \xi_{it} \tag{16}$$

Where $Land_{it}$ denotes the urban land intensive utilization level; X denotes the explanatory variables, which include the core explanatory factor of urban digitalization level and the control variables p , the spatially lagged regression coefficient, measuring how much land intensive usage in neighboring areas affects each other; β_0 , the explanatory variable's regression coefficient; α_0 stands for the constant term; γ shows the spatially lagged regression

coefficient of the explanatory variables; μ_i denotes the area effect; λ_t indicates the time effect; and ξ_{it} is a random disturbance term.

(2) Spatial weight matrix (W). We refer to the available literature (Li et al., 2021; Zhao and Wang, 2022) and use the Durbin model, conducted under four spatial weight matrices, for empirical exploration. The four spatial weight matrices are the economic weight matrix, geographic adjacency weight matrix, geographic distance weight matrix, and economic-geographic nested weight matrix. The detailed calculation process can be referred to Ma et al. (2023a, 2023b) (Ma et al., 2023c).

(3) Variable selection. After combing through a large amount of previous literature (Tan et al., 2022; Wang et al., 2021a; Yang et al., 2022; Zhao et al., 2022), it was found that scholars in various fields have extensively and thoroughly explored the influencing factors of land intensive utilization, mainly involving four aspects: the industrial structure of cities, urban urbanization rate, urban economic development level, as well as environmental regulation level. Therefore, according to the available models and theories, this study integrates the relevant research results on land intensive use in cities and adds other dependent variables, such as urban innovation level, besides the core explanatory variable of urban digitalization level, to be more scientific and accurate, as shown in Table 4

Result

The temporal evolution of urban digitalization. The findings are revealed in Fig. 3, obtained with the total values measured by the Entropy-TOPSIS Model and according to the principle-breakpoint analysis to understand the characteristics of the development of the digitalization process in cities. The figure shows that digitization has typically progressed over time, and the number of cities at a more advanced stage has increased. Especially in 2014–2017, the number of cities with improved digitalization development is relatively high. From 2011 to 2020, the number of cities with low digitalization levels ($dig \leq 0.2$) decreased from 91 to 34, and the number of cities with high digitalization levels ($dig > 0.5$) increased from 1 to 8. At the beginning of the study, cities in the Yangtze River Economic Belt (110 cities) were dominated by low digitalization ($dig \leq 0.2$), accounting for about 82.73%. At the study's end, the urban digitalization level increased significantly, and cities at ($0.2 < dig \leq 0.35$) stage became mainstream with a total number of 43, accounting for about 39% of the total, while only 34 cities at a

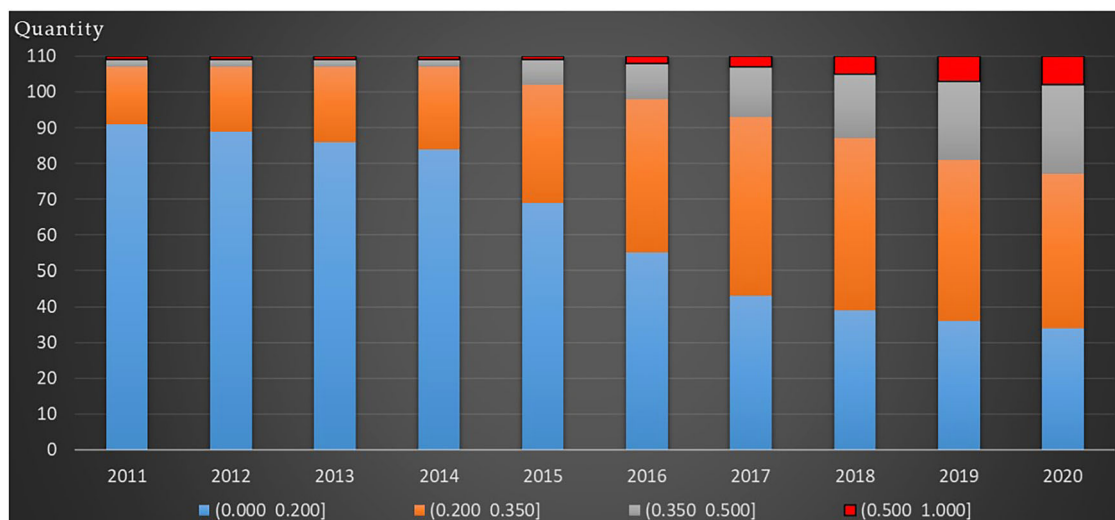


Fig. 3 The time evolution of the digitalization level of cities in the Yangtze River Economic Belt.

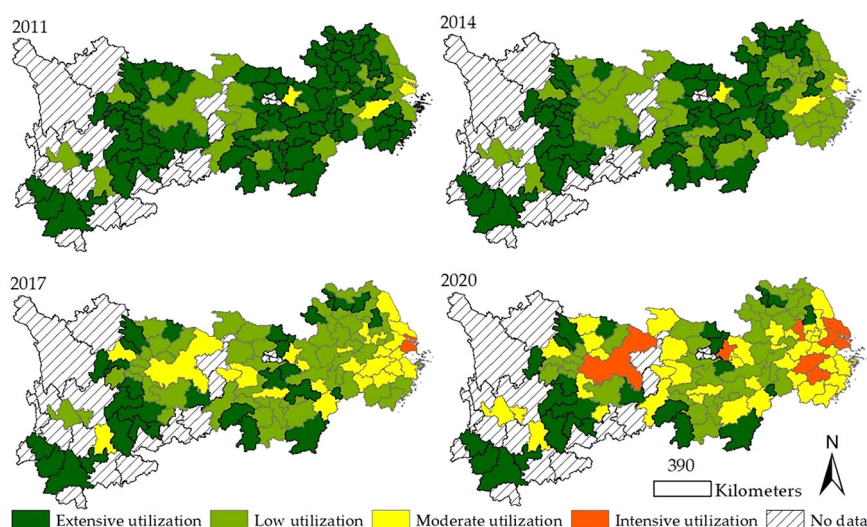


Fig. 4 Spatial and temporal evolution of urban land intensive use in the Yangtze River Economic Belt. The base map for the map is from Natural Earth (<http://www.naturalearthdata.com/>).

low level, accounting for about 31%. The remaining cities are in the stage of developing toward a higher urban digitalization level.

Spatial distribution characteristics of urban land intensive use.

To explore the distribution characteristics of urban land intensive use in China, based on the natural breakpoint approach, each city's measured comprehensive degree of land-intensive utilization was classified into four stages: less than 0.3 (Extensive utilization), 0.3–0.5 (Low utilization), 0.5–0.7 (Moderate utilization) and more than 0.7 (Intensive utilization). This paper uses *Arc-GIS10.6* software to visualize and draw Fig. 4. On the whole, the pattern of urban land-intensive utilization level shows an apparent difference between East and West, which may be related to the differences in industrial structure, economic development level, and geographical environment between east and west. A relatively high intensive urban land utilization level is also evident in the central cities of Chengdu-Chongqing urban agglomeration, the Yangtze River Delta urban agglomeration, and the primary urban agglomeration represented by Wuhan. These regions have higher industrialization and urban economic development, high urbanization rates, better industrial structure, better high-tech

and other industries development, and a generally higher digitalization level. The intensive urban land utilization level has risen significantly over time.

Dynamic transition characteristics of urban land intensive utilization levels.

To explore the transition dynamics and vitality of urban land intensive utilization levels, the paper applies the Markov chain method to measure the probabilities of transferring between land-intensive utilization tiers during 2011–2020, whose results can be found in Table 5. Overall, the internal mobility of all urban land-intensive utilization levels is generally low. The central diagonal values reflect the probability that the stratum of land-intensive utilization level remains constant. The probability values of the main diagonal show that Extensive utilization (E) has the highest likelihood of stratum shift, which decreases further with the advance of the stratum. The diagonal values are above 0.80, reflecting the more obvious cascading solidification of the intensive urban land utilization level. The values above the main diagonal show the likelihood of an upward change in land-intensive utilization, which moves primarily upward. Still, the possibility is low; the highest is only 0.1799, and the probability of

Table 5 Markov transition probability matrix ($k = 4$).					
	Sample size	E	L	M	I
E	378	0.8122	0.1799	0.0079	0
L	336	0.0000	0.8155	0.1786	0.0059
M	249	0.0000	0.0080	0.8835	0.1084
I	27	0.0000	0.0000	0.0741	0.9259

E is Extensive utilization, L is Low utilization, M is Moderate utilization, I is Intensive utilization. The bold values show the statistical proportion of the status quo, visual prominence of critical data and cross-comparison of key results.

Table 6 Moran's I statistics of the urban land intensive use.				
Year	Adjacency matrix	Geographic weight matrix	Economic weight matrix	Economic-Geographic Nested Matrix
2011	0.311***	0.091*	0.127**	0.101*
2012	0.301**	0.106*	0.129*	0.103*
2013	0.297*	0.102	0.106*	0.102
2014	0.286*	0.098*	0.098*	0.097*
2015	0.266*	0.101	0.126*	0.113
2016	0.229*	0.089	0.097	0.090
2017	0.196**	0.073*	0.089*	0.079*
2018	0.202*	0.067	0.103	0.064
2019	0.197**	0.050*	0.084*	0.061*
2020	0.188**	0.046*	0.072	0.062*

The significance levels denoted by ***, **, and * are 1%, 5%, and 10%, respectively.

change across two tiers is less than 0.079, which suggests that the advancement of land intensive use levels in cities is steady and gradual. It isn't easy to make a multi-level leapfrog development. The downward shift occurs only in the Moderate utilization and Intensive utilization tiers, and the probability of both is less than 7.5%. This demonstrates that the decline in the stratum of urban land intensive usage occurs only at high levels, with a low chance of occurrence.

Analysis of spatial autocorrelation characteristics of urban land intensive use. Since the classification of urban land intensive utilization in the Yangtze River Economic Belt has been clarified, it is also vital to investigate its specific characteristics to understand its primary spatial differentiation and provide practical recommendations and a policy foundation for eliminating regional disparities.

Global spatial autocorrelation analysis of urban land intensive use. According to the global spatial autocorrelation formula (12), Moran's *I* index is obtained under four different spatial weight matrices using *Geoda* software, as shown in Table 6. Under the spatial adjacency weights, the land-intensive use level of cities in the Yangtze River Economic Belt all passed the spatial autocorrelation test at the 0.05 significance level. All of Moran's *I* index values were more than 0.18. Under the remaining three spatial weight matrices, spatial autocorrelation also existed in most years of the study period. From the longitudinal latitude of development, Moran's *I* index of spatial autocorrelation became smaller overall, from 0.311 at the beginning to 0.188 at the end, showing a gradual weakening trend. However, Moran's *I* index was positive in all cases, indicating an overall positive spatial correlation. Similar results were obtained for the remaining three spatial weight matrix conditions, consistent with previous research findings (Luo et al., 2022). This also shows from one side that under the national urban agglomeration strategy, urban

agglomerations such as those in the Yangtze River's upper, middle, and lower reaches play a role in the new round of regional integration. The regional synergistic development pattern is gradually formed, which beneficially promotes the balanced development of land-intensive use among cities.

Local spatial autocorrelation analysis of urban land intensive use. Moran's *I* index for global spatial autocorrelation is an overall regional metric that merely indicates the average degree of the spatial relationship between a unit and its surroundings. To further determine the local spatial clustering or the spatial location of anomalies of land-intensive use levels, the regional autocorrelation analysis approach (Eq. 13) is used in this study to assess and visualize the spatial pattern of LISA for land-intensive usage levels at the 0.05 significance level (Fig. 5). Since the survey is a long process. The overall spatial correlation of land intensive utilization level in the study region is weakened. We select the initial 2011 and the final 2020 land use efficiency to analyze its local spatial correlation evolution characteristics.

At the significance level of 0.05, most H-H accumulations are found in the downstream provinces of Shanghai, Jiangsu, and Zhejiang. The high economic development level, good primary conditions of construction land, capital surplus, and sufficient non-agricultural labor population in the Yangtze River Delta elevate the degree of urban land intensive use to a higher level. These cities have high land use efficiency values for themselves and neighboring cities, and the difference between their efficiency values and those of neighboring cities decreases as they have a significant favorable influence on the surrounding cities. It is essential to note in particular that the period 2011–2020 shows an H-H zone in Yunnan Province, where the city of Kunming is located, with a high level of intensive land use, and its surrounding cities show a spatial aggregation phenomenon, which is a rare and strange result in Yunnan Province as it is generally a low-level region. The following are some possible explanations: on the one hand, Kunming and its neighboring cities further optimize their development due to rapid innovative growth, reasonable capital allocation, optimized industrial structure layout, and rapid improvement of urban digitalization, etc., which leads to increased in land intensive utilization and an immediate improvement in the surrounding region; on the other hand, as a demonstration area for mountainous city construction in China, urban development is less dependent on construction land input. Even with little investment in urban construction land, it can ensure a certain economic output level and improve regional land use. After nearly ten years of development and radiation, the H-H agglomeration area was eventually formed, but basically, no significant changes occurred in other regions of Yunnan Province. There is also a slight contraction in the range of L-L agglomeration. L-L type areas are distributed in inland cities in Yunnan and other provinces with relatively poor location conditions, low economic output per unit of construction land, and inadequate industrial economic efficiency. Both cities' and neighboring cities' land-intensive use level values are shared, showing a positive spatial correlation of low values. The H-L agglomeration area appears in Chongqing, which significantly differs in land utilization efficiency from that of neighboring cities: its efficiency is high. In contrast, the neighboring cities have low land use level values. The L-H agglomeration area is found in Xuancheng City, Anhui Province, indicating that the city has an ordinary land utilization level. In contrast, the neighboring cities have a high land use level, and the geographical disparities in land usage values between them and their neighboring cities are significant. L-H and H-L agglomeration's scope has significantly altered during the past decade. The local correlation of urban land-intensive usage level in the Yangtze River Economic Belt

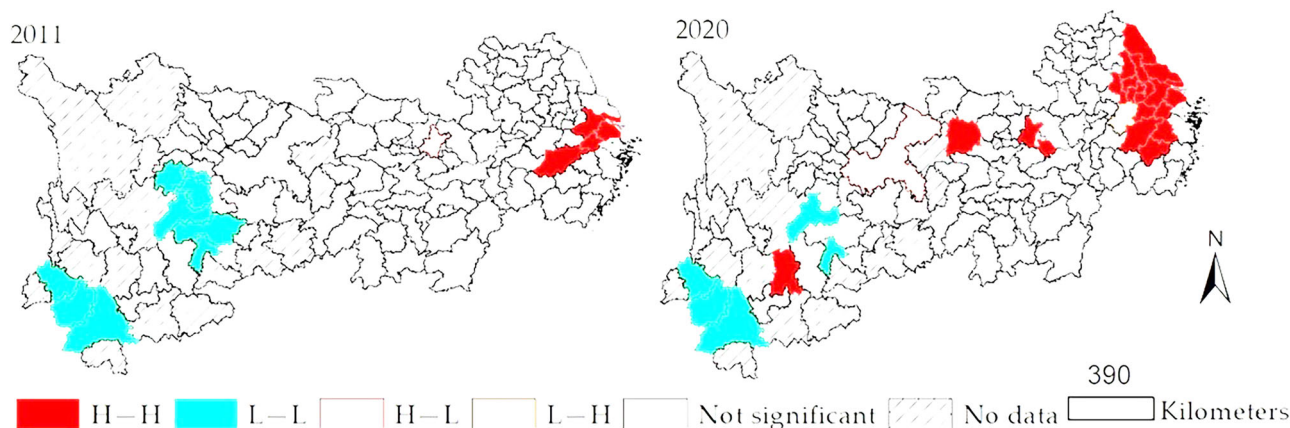


Fig. 5 LISA cluster map of urban land intensive use level in the Yangtze River Economic Belt in 2011 and 2020. The base map for the map is from Natural Earth (<http://www.naturalearthdata.com/>).

shows the phenomenon of “large agglomeration and large dispersion.” Although the differences in land-intensive use levels between the upper, middle, and lower reaches of the Yangtze River Economic Belt have narrowed, their coordinated development still needs further strengthening.

Effect of digitalization on intensive land use. First and foremost, the Wald and LR tests were performed in this study, and the findings revealed that both passed the significance test at 1%, contradicting the original premise of utilizing the SLM or SEM method, suggesting that the spatial error and spatial lag terms are included simultaneously. As a result, the spatial Durbin model (SDM) is applied in this work to conduct the analysis. The fixed-effects model is preferable if the estimated Hausman results satisfy the 1% significance test. Because of the spatial correlation, making reliable estimations with the usual OLS approach is difficult, so the new Quasi-Maximum Likelihood estimation (QMLE) method is utilized for calculation, with the final model estimates provided in Table 7. From Table 7, the coefficients of the effects of digitalisation on urban land intensive utilisation level are significantly positive under all four weights, which indicates that digitalisation promotion can dramatically enhance the intensive land utilisation level in the region. In the digital development process, enterprises’ overall performance can be improved (Fernandes et al., 2019), significantly enhancing regional industries’ status and thus improving the level of intensive land usage. Meanwhile, digitalization’s gradual penetration of the Internet of Things and big data makes urban resource allocation more efficient. It generates economic externalities, which lead to the optimization of industrial layout, the advancement of production efficiency, higher urban energy use efficiency, a better environment, and further enhancement of the ecological and economic benefits of land, thus finally promoting the progress of the intensive land use level. In conclusion, digitalization can beneficially enhance the intensity of land use, optimize land’s structural layout, improve its economic benefits, further rationalize its social benefits, and significantly improve its ecological benefits. Thus, digitalization positively affects the economy, society, and ecology of land in cities, which contributes well to enhancing urban land intensive utilization.

Regarding the control variables, the coefficient and significance of urban innovation capacity (*oil*) change slightly under different spatial weight matrices. With the adjacency weight matrix, the urban innovation capability positively affects intensive urban land use in neighboring areas. This may be because the technological progress brought by innovation promotes effective planning and land use efficiency, promoting the intensive land utilization level. Meanwhile, under the neighborhood weight matrix, the invention

has the most significant influence on the intensive utilization of land in cities, probably due to the most critical spatial spillover between neighbors, driving a substantial increase in the intensive land usage level.

The industrial structure (*ind*) passed the significance test under the adjacency matrix and the geographical weight matrix, beneficially promoting the intensive land utilization level in the region in both cases but hurting the neighborhood. It is possible that, as a result of the siphoning development of urban industrial agglomeration and the upgrading of the local industrial structure, some low-end backward enterprises and industries are seriously hit at the same time, causing them to move to the neighboring cities for survival, thus leading to a negative impact on the neighboring towns. This also explains precisely why the spillover effects are not evident in the economic weight and geography nested matrix.

Although there are some differences under the four weights, the coefficients of the urban urbanization level variable show that they are beneficial to improving urban land-intensive usage. This suggests that, despite the Yangtze River Economic Belt’s urbanization level being above China’s median level after years of development, it still has to be enhanced to support further development of the intensive land use level.

Environmental regulation (*erp*) passes the significance test only under the geographic adjacency matrix. It benefits intensive land usage but has a more significant negative impact on surrounding cities. This is because when environmental regulation is strengthened in a city, it inevitably raises the cost of units and industries with high pollution emission needs, which leads to a sure migration of pollution sources, especially to neighboring cities, and therefore inevitably brings adverse effects to neighboring cities. The increase in economic development (*pgdp*) exerts a less pronounced impact on intensive land usage, yet the adverse effects of spillover are noticeable. This may be associated with the competitive development among various cities in China and the need for more unified coordination among cities that are beggar-thy-neighbor.

Spatial heterogeneity analysis. This study is undertaken from two perspectives, namely, regions, agglomeration or non-agglomeration, to explore further spatial heterogeneity in digitalization’s effects on urban land-intensive use. The division of areas (corresponding to the upper, middle, and lower reaches of the Yangtze River Economic Belt) and urban agglomerations (three national-level urban agglomerations, namely the Chengdu-Chongqing urban agglomeration, Yangtze River Delta urban agglomeration, and Yangtze River midstream urban agglomeration, were selected) was primarily

Table 7 Regression of results.									
Explanatory variables	Adjacency matrix		Geographical weight matrix		Economic weight matrix		Economic geography nested matrix		
	x	W × x	x	W × x	x	W × x	x	W × x	
dig	0.112** (2.151)	0.049* (1.691)	0.101* (1.908)	0.059* (1.869)	0.095* (1.926)	0.019 (1.480)	0.142* (1.955)	0.034 (0.252)	
uil	0.159** (1.811)	0.066*** (2.764)	0.118** (1.686)	0.040* (1.762)	0.104* (1.952)	0.037 (1.325)	0.100* (1.896)	0.012 (0.976)	
ind	0.042* (1.893)	-0.041* (-1.739)	0.056** (3.379)	-0.232* (-1.844)	-0.047*** (-3.011)	-0.045 (-1.551)	0.036* (1.814)	-0.034 (-1.018)	
urb	0.039* (1.689)	0.049*** (4.546)	0.014* (1.751)	0.132*** (3.266)	0.017** (2.006)	0.049 (1.433)	0.020* (1.713)	0.039 (1.003)	
erp	0.008* (1.785)	-0.052** (-3.075)	0.004 (0.094)	-0.107* (-1.793)	-0.041 (-1.011)	0.125 (1.368)	0.002 (0.489)	-0.043 (-0.799)	
pgdp	0.005 (0.183)	-0.091* (-1.657)	-0.021 (-0.630)	-0.228** (-3.461)	-0.053 (-1.442)	-0.029*** (-2.907)	-0.041 (-1.102)	-0.034*** (-2.910)	
rho		0.561*** (19.971)		0.797*** (36.570)				0.124*** (4.028)	
City FE		YES		YES				YES	
Year FE		YES		YES				YES	
Observations		1100		1100				1100	
R-squared		0.342		0.274				0.296	
log-likelihood		2350.959		2196.613				2117.234	
***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The values in parentheses are t-statistics.									

referred to the existing relevant documents and literature in China (Ma et al., 2023b). As the effect of spatial heterogeneity was considered, the subsequent study unfolded the estimation based on the geographic weight matrix. To determine whether there is regional heterogeneity in the influence of digitalization on the degree of intensive urban land use, three regions from the upper, middle, and lower reaches of the Yangtze River Economic Belt are analyzed, and the results are displayed in Table 8.

Digitalization significantly raises the degree of intense urban land use in the downstream region and dramatically improves intensive land use in surrounding cities. This could be because downstream cities have more apparent benefits in digital infrastructure and digital sector development. Furthermore, as the downstream region is rich in digital innovation talent and capital, it can better play the role of digital empowerment with various benefits while also considerably improving the degree of urban land intensive usage. Digitalization development in the midstream region can enhance the degree of urban land usage and impact nearby areas. This could be because cities in the midstream region are still in the early stages of rapid digital development, and the industrial layout and regional functions provided by digital infrastructure construction in cities are more rational, as is the improvement of land usage efficiency. Additionally, the midstream region's major cities have apparent advantages. During the growth process, the core cities make the urban agglomeration spillover more evident due to their diffusion and driving effect, thus promoting the spillover effect generated by digital development. The digitalization development variables in the upstream region did not pass the significance test, most likely because the digital product in the upstream region is still in the primary stage with a low level (see Fig. 2). Since diffusion effect cannot be formed after the scale and accumulation, and since digital empowerment yields little in the way of products, the influence of digitalization on the level of land-intensive urban usage is insignificant.

According to urban agglomeration heterogeneity, digital development within urban agglomerations significantly contributes to urban land intensive use. The effects of spillover may encourage better land use in nearby areas. The result of digitalization has no appreciable impact on boosting urban land intensive usage in non-urban agglomeration regions. This is primarily because the scale and agglomeration effects have been established initially, and the digitalization level of cities in urban agglomerations is typically relatively high (see Fig. 1). There are preferential strategies inside urban agglomerations, such as policy cooperation and resource pooling, to promote their land intensive usage level. In contrast, cities in non-urban aggregations are not significantly enhanced in terms of urban land intensification due to their unfavorable geographical location and limited resources, as well as the fact that most of them are in the infancy of digitalization. Intuitively, it can also be well verified by the spatial evolution of urban land intensive usage level in Fig. 3.

As a result, given the spatial-regional heterogeneity, cities in downstream areas and urban agglomerations have more fully unleashed digital dividends, and the influence of digitalization on urban land-intensive use is more pronounced. In contrast, upstream and non-urban agglomeration cities have a less prominent digital role.

Robust test. To enhance the reliability of the research findings, this study systematically validates the conclusions through a multi-dimensional approach. First, a two-way fixed effects Spatial Durbin Model is constructed, with cross-validation conducted using four spatial matrices (Adjacency matrix, Geographical weight matrix, Economic weight matrix, and Economic

Table 8 Regression results of the spatial heterogeneity test.

Explanatory variables	Upstream region	Midstream region	Downstream region	Urban Agglomeration	Non-Urban Agglomeration
<i>dig</i>	0.087 (1.021)	0.091** (2.044)	0.106*** (3.315)	0.198*** (3.172)	0.094 (0.867)
W × <i>dig</i>	0.041 (1.107)	0.059* (1.937)	0.078** (2.074)	0.117*** (3.303)	0.042 (1.105)
Control	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	330	360	410	670	430
R-squared	0.074	0.104	0.198	0.125	0.091
log-likelihood	1128.812	1094.832	1039.751	1155.916	1090.132

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The values in parentheses are t-statistics.

Table 9 Robustness Test Results.

Explanatory variables	Tests for sample heterogeneity	Robustness checks with alternative measures		Lagged independent variable by one period
	(1)	(2)	(3)	(4)
<i>dig</i>	0.101** (2.101)		0.134** (2.323)	0.185** (2.137)
W × <i>dig</i>	0.044* (1.790)		0.074*** (2.751)	0.100** (2.003)
<i>ddig</i>		0.080* (1.890)		
W × <i>ddig</i>		0.040* (1.700)		
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	1020	1100	1100	990
R-squared	0.404	0.302	0.524	0.399
log-likelihood	1202.320	1004.975	1198.205	1193.017

***, **, and * represent significance levels of 1%, 5%, and 10%, respectively. The values in parentheses are t-statistics.

geography nested matrix). Second, multidimensional control variables are systematically incorporated to mitigate omitted variable bias. Finally, the robustness of the conclusions is reinforced through the following triple tests, all of which are based on the adjacency spatial matrix.

Sample heterogeneity test. Given that municipalities directly under the central government (e.g., Chongqing and Shanghai) and sub-provincial cities (e.g., Hangzhou and Nanjing) possess administrative hierarchy advantages and resource concentration characteristics (Xu and Shan, 2024), their land market maturity and digital technology adoption levels may significantly exceed those of ordinary prefecture-level cities, potentially introducing sample selection bias. To address this, the study excludes samples from two municipalities and six sub-provincial cities, retaining data from 102 prefecture-level cities for re-examination. As shown in column (1) of Table 9, the core variables' coefficient direction and significance levels remain materially unchanged, confirming that the findings are robust to excluding unique samples.

Variable measurement substitution test. To address limitations inherent in single measurement methods, alternative metrics are adopted for key variables. For the independent variable, the urban digital economy development index (*ddig*) constructed by Zhao et al. (2020) (Tao et al., 2020) is employed, as its indicator system aligns closely with urban digitalization levels. The substitution results in column (2) of Table 9 confirm consistency. For the dependent variable, land-intensive utilization is redefined using classical principal component analysis. Regression results in column (3) of Table 9 demonstrate that the core explanatory variable retains statistical significance, corroborating the robustness of the original conclusions.

Endogeneity remediation test. To address potential reverse causality—where improved land use efficiency may reciprocally drive digitalization—this study adopts the lagged variable approach of Shao et al. (2022) (Shuai et al., 2022), introducing a one-period lag for the explanatory variable. This dynamic specification mitigates model bias and captures the time-lagged effects of digitalization. Empirical results in column (4) of Table 9 reveal that the lagged term's coefficient direction and significance levels closely align with contemporaneous estimates, indicating effective endogeneity control.

Through these systematic checks, the coefficient directions, statistical significance, and economic interpretations of core variables remain stable, demonstrating strong robustness in the findings. This multi-pronged validation further provides robust empirical support for the causal inference that digitalization intensifies land use.

Discussion

In-depth spatiotemporal analysis of ULIU. It can be seen from Fig. 3 that the ULIU has been improving, and the number of cities in the Extensive utilization stage is significantly reduced, while the Intensive utilization in the high setting has been growing from none, and the number is increasing sharply. The Markov transition matrix in Table 5 shows that the ULIU of most cities remains in the same place. However, there is still more than 10% of the proportion of the leap to the up level, and of course, there are a few leaps to the next level and regression after the highest stage. It can be found from Fig. 4 that ULIU has apparent high and low agglomeration imagination. From the above spatio-temporal development phenomena, we can see that the development of ULIU is on the rise, and spatial agglomeration and

urban agglomeration effects are present (Table 8). From the existing research, it can be found that the development of ULIU is the result of the comprehensive impact of many influencing factors such as city size (Mao et al., 2023), urbanization level (Yang et al., 2023a; Zhang et al., 2023e), economic development (Jing et al., 2020; Zhang et al., 2022a), industrial structure (Lan et al., 2023; Ye et al., 2023) and environmental regulation (Ma et al., 2023a). Table 7 of this study further proves that local cities and the positive influence and reverse dual effects of surrounding cities. Among them, economic development, optimization and upgrading of industrial structure, and environmental regulation have dragged down the improvement of ULIU in the surrounding cities. The economic distance matrix in Table 7 can also illustrate this point. Of course, the progress of ULIU is also affected by carbon emissions (Wang et al., 2023a; Yu et al., 2023), the ecological environment, and so on. Therefore, we find that ULIU is involved in many ways while the urban land use in the YREB is improving; Hence, the positive factors affecting it are the main ones.

How does the development of urban digitalization influence ULIU. With continuous iteration and updating of digital technology (Moufid et al., 2025), digital industrialization, and industrial digitalization going hand in hand (Ma et al., 2023b), and the comprehensive expansion of the digital economy, digitalization development shows a specific positive effect on city ULIU. Also, spatial spillover offers an excellent positive impact on surrounding municipalities.

The higher the level of digitalization in a region, the higher the level of digital economic development is (Fan et al., 2023b). The digital economy relies on the application of new technologies such as the Internet of Things, Big data, Cloud computing, and Artificial intelligence (Bai et al., 2023a). It affects land factors from the source and reduces the mismatch rate of land production factors through data elements, including data analysis of soil, production factors such as renewal required in land use, physical action on land factors, and improvement of the input efficiency of land factors. Thus, the level of intensive land use can be improved. At the same time, digital technology's zero marginal cost advantage will magnify the economies of scale and scope of data elements and accelerate the association, complexity, refinement, and networking of data elements (Calderon-Monge and Ribeiro-Soriano, 2023) and land elements. This factor interaction will further increase the superposition and saturation of land use, thus increasing land use. Secondly, the entry into the process of enterprise production and operation. Compared with the traditional economy, the digital economy can significantly reduce human production and life dependence on time and space, employing communication technology and information networks in production (Du et al., 2023). Multiple functions of living (Calderon-Monge and Ribeiro-Soriano, 2023), working, and leisure appear simultaneously in unit land. The land use function shows a compatibility trend, improving the intensification and three-dimensional degree of land use. The efficiency of urban land use and sustainable development levels have significantly improved. Thus, the level of intensive land use is increased.

Due to the development of digitalization, people's way of life has been dramatically changed (Christmann and Schinagl, 2023; Vial, 2019), and people's living standards have been improved. Digital innovation is the driving force, digital technology is the support, and industrial chain modularisation is the core (Matt et al., 2023), supporting forming a new economic structure. In China's unique pattern of "double circulation," consumption upgrading is the general trend, and consumption drives supply-side reform and development. It effectively drives the traditional

business model to carry out the new economic structure era (Ritter and Pedersen, 2020), which leads to people's higher requirements for the urban environment (Bai et al., 2023b) and public service quality (especially in the aspects of environmental friendliness ecology and (Yang et al., 2023c; Zhou et al., 2023) ecological resources water (He et al., 2023; Yuan, Wu, et al., 2023)), thus promoting the improvement of urban land use level.

Conclusions and recommendations

Conclusion. This study examines the spatial evolution characteristics of digitalization development and the intensity of urban land use within cities of the Yangtze River Economic Belt. It further investigates the impact of digitalization on urban land intensity. The findings are as follows:

- (1) Urban digitalization development has transitioned from a scattered distribution to a clustered pattern, with advanced regions acting as hubs. While the digitalization level of most cities has increased, club convergence remains a defining feature of digital progress.
- (2) Urban land use patterns' spatial heterogeneity is influenced by economic, environmental, social, and local government factors, with a more pronounced difference between the upstream and downstream regions. The hierarchical dynamic transition is relatively smooth, with an apparent spatial clustering of urban land use intensity.
- (3) Urban digitalization significantly enhances land use intensity in the region and exhibits a notable spatial spillover effect. It positively affects the intensity of land use in neighboring cities. Regarding spatial distribution, urban digitalization in the middle and lower reaches and within urban clusters significantly boosts land use intensity, with a discernible spatial spillover effect.

Recommendations. In this study, each city's digitization and land intensive use level is measured by constructing an index system of urban digitization and land intensive use with the Entropy - TOPSIS model. On this basis, the spatial effect of digitalization development on urban land intensive use is analyzed, and the heterogeneous role of regions and urban agglomerations is explored. Thus, in addition to the theoretical implications of expanding the factors influencing the urban land-intensive use levels and supplementing the evidence of empirical studies, the findings of this study also have specific policy implications, which are suggested as follows:

- (1) The government should improve digital empowerment and consolidate digital infrastructure. It should encourage the development of next-generation information infrastructure, accelerate the implementation of higher-quality interconnection, and provide vital information infrastructure support for high-speed digital products, thereby expanding the scope of digital benefits in the broader area. Furthermore, the government should build an environmental regulation model that includes the entire population and broaden the role of digitalization in promoting the intensive use of urban land.
- (2) Strengthen the impact of technological innovation and other influence factors on urban land intensive use and enhance technical support capabilities. On the one hand, the government should increase the intensity of investment in innovative R&D, promote the R&D of technologies such as cloud computing, industrial internet, and big data, and improve the application and transformation of primary and public applicable technologies, thus improving the level of intensive land use; On the other hand, it should focus on

the improvement of energy use efficiency, catalyzes the emission reduction effect of technological innovation, and enhances the technical support capability. Thus, it indirectly promotes the advancement of land ecological efficiency, improving the land intensive use level to achieve a better life (Jiang et al., 2025).

- (3) The government should implement heterogeneous governance strategies based on regional development differences. Based on restricted endowments and the influence of digitalization on urban land intensive usage, it should adjust the pace of digital development in each area, break industry barriers and geographical restrictions of new models and business forms, and enhance the differences and synergy of digital governance in each region.

While this study advances scholarly understanding of the digitalization-land use intensity by addressing critical gaps in the existing literature and offering theoretical insights into how digital transformation fosters sustainable urban development, several limitations warrant attention. First, the composite index constructed to evaluate urban digital development—encompassing digital infrastructure, application maturity, industrial digitization, and fintech penetration—faces dual constraints: (1) data availability issues that may compromise measurement precision, and (2) insufficient accommodation of regional heterogeneity in digitalization's spatial impacts. Future investigations could employ enhanced digital metrics and typological frameworks to enable granular, city-level analyses of mechanistic pathways, particularly in municipalities with robust digital trace datasets. Second, although we identify key mechanisms through which digitalization influences land-intensive use patterns, the empirical validation requires deeper exploration. Subsequent research should prioritize (1) developing formalized theoretical instruments to quantify digitalization's multidimensional effects and (2) establishing causal identification strategies that disentangle technology-driven land use optimization from confounding socioeconomic factors.

Data availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Received: 25 November 2024; Accepted: 29 May 2025;

Published online: 18 June 2025

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Author contributions

Writing—draft and project administration, LM; investigation, SD; Data curation, writing, SD, YH, and LM. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Informed consent

This article contains no studies with human participants performed by any authors. All authors confirm the version of the manuscript. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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