NONLINEAR EFFECTS OF THE DIGITAL ECONOMY ON URBAN LOW-CARBON ECOLOGICAL HIGH-QUALITY DEVELOPMENT IN CHINA: A MACHINE LEARNING-BASED ANALYSIS AND PREDICTION

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Abstract. The digital economy development (DED) plays a crucial role in promoting urban low-carbon ecological high-quality development (ULCEHD). This study uses panel data from Chinese prefecture-level regions between 2014 and 2023. It employs a Bayesian Graph Convolutional Neural Network (BGCNN) model to explore the nonlinear and spatially heterogeneous effects of DED on ULCEHD while controlling confounding variables. A spatiotemporal dynamic entropy method is proposed to quantitatively measure DED and ULCEHD in this study, revealing significant upward trends in both metrics from 2014 to 2023. The findings demonstrate an "S-shaped" relationship between DED and ULCEHD, where initial increases in DED lead to ULCEHD improvements of 0.02 units per 0.10 DED increase; this effect intensifies to a 0.20 rise at medium levels of DED, followed by a plateau. Spatial analysis reveals significant regional disparities, with the strongest DED impacts on ULCEHD observed in central, southwestern, and northeastern China. Conversely, regions such as the North China Plain and parts of the eastern coast exhibit weaker DED effects on ULCEHD. By 2030, DED is expected to spread more evenly across China. This will lead to broader ULCEHD improvements, highlighting the need for region-specific policies to fully leverage digital economic growth for sustainable urban development.
Keywords: *spatiotemporal dynamic entropy weight (STDEW), Bayesian graph convolutional neural network (BGCNN), prediction, spatiotemporal distribution, spatial heterogeneity, spatial heterogeneity*

Introduction

In recent years, the burgeoning advancement of digital technologies—including artificial intelligence, big data, cloud computing, and blockchain—has fueled the global growth of the digital economy development (DED) (Agarwal et al., 2021), establishing it as a critical impetus for economic expansion, industrial modernization, and societal advancement (Mesenbourg, 2001). Defined as an economic ecosystem that leverages digitized information, advanced information networks, and information and communication technologies (ICT) as pivotal production factors, the DED aims to increase efficiency and optimize industrial structures (Vermesan and Friess, 2013).

In China, the DED has undergone an exponential increase, surging from 11 trillion RMB (approximately 1.6 trillion USD) in 2012 to 35.8 trillion RMB (roughly 5 trillion USD) in 2018, thereby constituting over one-third of the country's gross domestic product (GDP) (Zhang et al., 2021). According to the China Academy of Information and Communications Technology (CAICT), core digital industries—including ICT manufacturing, e-commerce, internet finance, cloud computing, and big data services—have emerged as pivotal drivers of China's economic growth and industrial transformation in recent years (Chen and Yang, 2022). National development policies, such as "Internet

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Plus," mass entrepreneurship, innovation initiatives, and the "Made in China 2025" strategy, aim to stimulate digital transformation across various economic sectors in China (Zenglein and Holzmann, 2019).

Concurrently, the emphasis on urban low-carbon ecological high-quality development (ULCEHD), which focuses on environmental sustainability, resource efficiency, and ecological civilization, has become a top strategic priority for China's quest for high-quality growth (Gao et al., 2021). ULCEHD refers to an integrated urban development index that combines low-carbon transition, ecological preservation, and high-quality economic growth, emphasizing sustainability and innovation. Green economic efficiency focuses on maximizing economic output relative to environmental input, using indicators such as energy intensity or carbon productivity to evaluate ecological performance. Digital industrialization denotes the transformation of traditional industries through digital technologies like AI and big data, enabling productivity gains and structural upgrading. In contrast, green development is a broader concept that promotes harmony between economic and environmental systems, often serving as a guiding philosophy rather than a measurable outcome. While ULCEHD reflects a specific urban implementation path of green development, it places greater emphasis on integrated governance and measurable urban performance outcomes. Since the 18th National Congress of the Communist Party of China (CPC) in 2012, the central government has elevated ecological progress to national significance, propelling green transformations across diverse sectors (Chen and Chen, 2022). Successive Five-Year Plans, from the 12th to the 14th, have instituted binding targets aimed at industrial structure optimization, resource efficiency improvements, pollutant discharge reductions, and the development of green technologies and industries (Guo, 2010). For example, the 14th Five-Year Plan (2021-2025) underscores the accelerated transition to a green and low-carbon economy as pivotal for achieving carbon neutrality by 2060. In recent years, the integration of the digital economy into regional development strategies has emerged as a critical driver for green innovation, enhancing green economic efficiency, and fostering high-quality economic development in China. The digital economy's influence on green innovation capabilities is profound, with research indicating a significant positive impact, particularly in regions with robust R&D investments (Dai et al., 2022). This effect is further corroborated by studies highlighting the digital economy's role in improving green economic efficiency through digital industrialization, suggesting that spatial spillover benefits are crucial for sustainable growth (Kong and Li, 2022). Moreover, the digital economy has been identified as a pivotal element in increasing China's Green Total Factor Productivity (GTFP), mainly through fostering technological innovation (Wang, 2023). Additionally, the spatial dynamics of the digital economy reveal its potential to bridge regional development disparities, contributing to high-quality economic development across different locales (Ding et al., 2021). At the city level, the digital economy's contribution to carbon emission reduction underscores the importance of spatial correlations and targeted policy measures for achieving carbon neutrality (Wang et al., 2022). The broader implications of these findings extend to rural revitalization and regional development strategies, emphasizing the necessity for differentiated approaches to harness the digital economy's full potential (Sidorov and Senchenko, 2020; Zhou et al., 2023).

DED influences ULCEHD through technological innovation, resource allocation efficiency, and environmental governance. In the early stages, DED promotes the growth of eco-friendly industries, optimizes market mechanisms, and strengthens real-time

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environmental management, leading to reductions in carbon emissions and improvements in ecological quality (Zhang et al., 2022; Lyu et al., 2024). As digitalization deepens, its positive effects accelerate due to economies of scale and the diffusion of green technologies. However, beyond a certain threshold, negative externalities such as high energy consumption from digital infrastructure, data privacy concerns, and regulatory inefficiencies may emerge (Li et al., 2023). These dynamics result in an S-shaped nonlinear relationship: slow initial growth, rapid improvement, and eventual plateauing or decline in ULCEHD as the digital economy matures and its marginal ecological benefits taper off.

Internationally, the intersection between DED and sustainability has garnered increasing scholarly attention. Studies in OECD countries have demonstrated that digital technologies can enhance environmental performance by improving energy efficiency, optimizing logistics, and enabling smarter resource management (Karlilar et al., 2023). In the United States, empirical research highlights how smart city technologies and digital governance tools contribute to carbon mitigation and urban sustainability (Nam and Pardo, 2011). Similarly, in developing economies, such as India and Brazil, the digital economy has supported low-carbon development by promoting inclusive access to clean energy, efficient supply chains, and decentralized environmental monitoring (Jung, 2015; Saini and Kharb, 2025). Moreover, the heterogeneous effects across countries and regions—shaped by institutional capacity, digital readiness, and environmental regulation—suggest the need for context-specific approaches (Albaity and Awad, 2023; Chen and Xing, 2025). These global findings underscore the importance of examining the spatial and nonlinear dynamics of DED's impact on sustainability outcomes in the Chinese context, where regional disparities and rapid digitalization create unique challenges and opportunities.

In China's development, DED and ULCEHD are closely intertwined, with digital technologies playing a crucial role in promoting sustainability across various sectors. Technologies like big data analytics and cloud computing allow for precise tracking and analysis of environmental performance, supporting eco-friendly decisions (Chen et al., 2014). The Internet of Things enhances resource efficiency by optimizing energy use, transportation, manufacturing, and building management (Moreno-Munoz et al., 2016). Artificial Intelligence and simulation modeling contribute to reducing resource consumption through predictive maintenance and virtual prototyping. Additionally, blockchain technology ensures transparency, traceability, and security in green value chains, from procurement to recycling (Saberi et al., 2019). These innovations collectively drive dematerialization, pollution reduction, and the circular economy, significantly aiding sustainable development.

Despite increasing interest in the DED and ULCEHD linkage, research gaps remain. Existing studies mainly use global regression models with broad data, missing the critical spatial spillovers and regional nuances driven by the dissemination of technology, policy, and capital. This approach overlooks the variable nature of the DED-ULCEHD relationship across regions, shaped by diverse resources, capabilities, and development phases. Furthermore, most research focuses on digitalization's singular impact on green metrics like energy use or emissions, neglecting the complex, bidirectional dynamics. The prevalent use of cross-sectional, single-year analyses also fails to capture the evolving DED-ULCEHD relationship over time. A significant shortfall is the absence of specific, actionable policy guidance based on the unique spatial and regional findings. To bridge these gaps, it's essential to employ spatial econometric and geospatial analyses, use panel

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data models that encompass both spatial and temporal aspects, and derive detailed strategies from spatial insights to guide localized digital-green initiatives.

To fill the above research gaps, this study aims to conduct a systematic investigation into the nonlinear and heterogeneous effect of DED on ULCEHD at prefecture-level in China from 2010 to 2022. By collecting and analyzing multi-source panel data of Chinese prefecture-level regions, and adopting spatial statistical method and Bayesian machine learning model, this study seeks to address three specific questions. What are the overall effects between DED and ULCEHD in China, and are there significant accelerating effects of DED on ULCEHD? How does their interrelationship differ by region considering contextual variations across cities? How can the empirical findings inform localized strategies and policy measures to promote coordinated digital-green transformation?

Methodology

Comprehensive measurement of DED and ULCEHD

DED

DED encompasses not only the ICT sector but also the digital transformation of traditional industries, e-commerce, and digital services. The IMF Working Paper "China's Digital Economy: Opportunities and Risks" suggests DED can be viewed through a narrow lens, focusing only on the ICT sector, or more broadly to include digitally transformed traditional sectors. Yet, the academic community lacks agreement on the metrics for measuring DED, highlighting the need for a methodologically sound and tailored indicator framework to accurately reflect DED's multifaceted nature (Baboo et al., 2022). Drawing on a comprehensive review of relevant literature, this study constructs an indicator system comprising nine metrics across three dimensions: digital infrastructure, digital industrialization, and digital innovation (*Table 1*).

Table 1. *Multi-level indicator framework for evaluating Digital Economy Development (DED)*

Primary indicator	Secondary indicator	Measurement	Unit
Digital infrastructure	Internet broadband penetration	Annual number of mobile phone subscribers	10^3 People
	Mobile phone penetration	Number of International Internet users	10^4 Households
	Total volume of postal services	Total volume of postal services in a city	10^4 CNY
Digital industrialization	Digital consumption	Total retail sales of urban social consumer goods	10^4 CNY
	Total volume of telecom business	Total volume of telecom business in a city	10^4 CNY
	Employment of urban units in the information transmission, computer services and software industries	Employment in the Information transmission, computer services, and software industries	People
Digital Innovation	Number of students enrolled in universities	Urban university students	People
	Quantity of educational resources	Educational employment	People
	Research and technical services employment at urban units	Research and technical services employment	People

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Digital infrastructure—including broadband internet, mobile telephony, and postal services—plays a foundational role in enabling digital participation and connectivity (Arvin and Pradhan, 2014). Broadband access, measured through fixed and wireless high-speed connections, support advanced digital activities such as cloud computing and data analytics, and is essential for high-bandwidth application (Czernich et al., 2011). Mobile subscriptions capture access to internet and application services, which especially important for expanding inclusion in developing regions (Hilbert, 2016). The readiness of postal and courier services facilitates e-commerce logistics, signals a city's capability to support digital trade. In terms of digital industrialization, metrics such as digital consumption sales and telecommunications service volume capture the scale and transformation of ICT-related sectors (Anusua and Sumit, 2004; Krasyuk et al., 2021). Employment in digital industries reflects job creation and skill development, which are crucial for sustaning digital transition and innovation capacity (Tambe and Hitt, 2012).

Digital innovation, driven by R&D and specialized knowledge, is a critical pillar of DED competitiveness (Bukht and Heeks, 2017). STEM education enrollment and investments in digital infrastructure, such as laboratories and technology parks, reflect the development of human capital and innovation ecosystem. These indicators not only meaure a region's potential for digital breakthroughs but also signal the long-term capacity for sustainable digital transformation (Moretti and Thulin, 2013; Hanushek and Woessmann, 2020). This comprehensive framework, spanning infrastructure, industrialization, and innovation, offers a robust basis for evaluating DED and guiding targeted policy interventions.

ULCEHD

The measurement of ULCEHD draws on multiple approaches, including green efficiency, individual indicator comparison, and multi-indicator composite scoring, in the absence of a universal standard for selecting metrics. Researchers emphasize that sustainability measures must align with specific goals, data availability, spatial scale, and developmental context (Huang et al., 2011; Pires and Fidélis, 2015). Tailoring variables to the research scope is vital, as applying generic framework may not capture the nuances of different development stages. For example, composite indices must be adapted to local conditions to ensure contextual relevance. The ULCEHD index in this paper encompasses three dimensions: green economy, green society, and green ecology, detailed in *Table 2*. Key measures include the share of tertiary sector production, economic growth rates, and industrial profitability, which jointly reflect the environmental and economic sustainability of regional development and economic restructuring. A higher proportion of the gross regional product from less energy and pollution-intensive services indicates a shift towards greener economic structures. Moreover, stable GDP growth rates serve as a proxy for ecological and economic stability, in contrast to volatile fluctuations.

Variable and method

Variables selection

The explained variable is ULCEHD, and the core explanatory variable is DED. To control for confounding effects, five control variables are included based on their theoretical relevance to urban sustainability and digital development. Economic development (GDP per capita) reflects financial capacity for green and digital investment; opening-up level (FDI) captures the influence of international technology and standards;

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urbanization level (URB) (measured by population density) relates to both ecological pressure and digital infrastructure needs; financial development level (FIN) (measured by loan-to-deposit ratio in financial institutions) indicates the availability of capital for green innovation; and government intervention (GOV) (measured by the proportion of public financial expenditure in the GDP) reflects policy support for sustainability and digitalization. These variables capture key economic, institutional, and demographic influences on ULCEHD. These variables comprehensively account for key economic, institutional, and demographic dimensions that influence both DED and ULCEHD, ensuring model validity. In addition, robustness checks are employed to further mitigate potential bias and reinforce the reliability of the empirical results.

Table 2. *Multi-level indicator system for assessing Urban Low-Carbon Ecological High-Quality Development (ULCEHD)*

Primary indicator	Secondary indicator	Measurement	Unit
Green economy	Percentage of tertiary production	Tertiary industry added value/GDP	%
	GDP growth rate	GDP growth rate	%
	Average profit of industrial enterprises	Profits of industrial enterprises/Number of industrial enterprises	10^4 CNY
Green society	Natural population growth rate	Natural population growth rate	%
	Registered urban unemployment rate	Registered urban unemployment/ Total labor force	%
	Average salary of employees on the job	Total Salaries of All Employees on the Job / Number of Employees on the Job	CNY
Green ecology	Carbon emission intensity	Carbon emission/GDP	Tons/10^4 CNY
	Air pollutants emission intensity	$PM_{2.5}$ emission/GDP	Tons/10^4 CNY
	Industrial waste water per GDP	Industrial wastewater discharge/GDP	Tons/10^4 CNY
	Industrial waste gas per GDP	Industrial SO_2 emissions/GDP	Tons/10^4 CNY
	Industrial waste dust per GDP	Industrial soot emissions/GDP	Tons/10^4 CNY

Data sources and descriptive statistics

The panel data at prefecture-level scale in China from 2014 to 2023 were collected from China city statistical yearbook and China statistical yearbook for regional economy. The descriptive statistics of variables are shown in *Table 3*. From a comparative perspective, both ULCEHD and DED have similar levels of relative variability, as indicated by their close CVs (0.27 for ULCEHD and 0.24 for DED). However, ULCEHD shows a slightly higher relative variability, suggesting that urban growth is influenced by

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a broader array of factors and is subject to greater fluctuations than domestic energy demand. The relatively lower variability in DED might indicate that energy demand is a more stable and predictable factor, potentially providing a consistent foundation that influences the more variable urban growth outcomes.

Table 3. *Descriptive statistics of explained, explanatory, and control variables used in the empirical analysis*

Types of variables	Variable	Mean	Std	Coefficient of variation	Min	Max
Explained variables	ULCEHD	0.41	0.11	0.27	0.19	0.87
Explanatory variables	DED	0.34	0.08	0.24	0.30	0.78
Control variables	ECO	54.54	127.45	2.34	5.304	6421.76
	OPN	98.50	223.19	2.26	33.01	3082.56
	URB	446.17	347.18	0.78	5.05	2759.14
	FIN	67.36	24.99	0.37	5.11	620.50
	GOV	22.52	25.28	1.12	1.14	604.06

The control variables exhibit much higher coefficients of variation, especially ECO (2.34) and OPN (2.26), indicating substantial relative variability. This high variability reflects significant diversity in economic conditions and trade openness across the sample, which could strongly impact the explained and explanatory variables. URB and FIN show lower CVs of 0.78 and 0.37, respectively, suggesting more moderate variability. GOV has a CV of 1.12, indicating that government expenditure or size varies considerably across the sample.

Spatiotemporal dynamic entropy weight method

For spatiotemporal data scenarios, the traditional entropy weight method cannot simultaneously capture variations in three critical dimensions: space, time, and space-time interaction. In response to this limitation, this study proposed a spatiotemporal dynamic entropy weight (STDEW) method as an advanced comprehensive evaluation approach. Compared with conventional evaluation methods—such as the static entropy method, coefficient of variation method, or principal component analysis—which often overlook dynamic spatial-temporal heterogeneity, the STDEW method fully integrates spatial differences, temporal evolution, and their interactive effects. It dynamically adjusts indicator weights based on the degree of variability across both spatial units and time periods, thus enhancing sensitivity to regional development patterns and temporal shifts. STDEW can be expressed as follows:

$$Y_{kit}^{(s)} = \begin{cases} \dfrac{y_{kit} - \min(y_{kit},\dots,y_{kNt})}{\max(y_{kit},\dots,y_{kNt}) - \min(y_{kit},\dots,y_{kNt})}, + \\ \dfrac{\min(y_{kit},\dots,y_{kNt}) - y_{kit}}{\max(y_{kit},\dots,y_{kNt}) - \min(y_{kit},\dots,y_{kNt})}, - \end{cases} \quad \text{(Eq.1)}$$

$$Y_{kit}^{(t)} = \begin{cases} \dfrac{y_{kit} - \min(y_{kit},\dots,y_{kiT})}{\max(y_{kit},\dots,y_{kiT}) - \min(y_{kit},\dots,y_{kiT})}, + \\ \dfrac{\min(y_{kit},\dots,y_{kiT}) - y_{kit}}{\max(y_{kit},\dots,y_{kiT}) - \min(y_{kit},\dots,y_{kiT})}, - \end{cases} \quad \text{(Eq.2)}$$

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$$Y_{kit}^{(st)} = \begin{cases} \frac{y_{kit}-\min(y_{kit},\dots,y_{kNT})}{\max(y_{kit},\dots,y_{kNT})-\min(y_{kit},\dots,y_{kNT})}, + \\ \frac{\min(y_{kit},\dots,y_{kNT})-y_{kit}}{\max(y_{kit},\dots,y_{kNT})-\min(y_{kit},\dots,y_{kNT})}, - \end{cases} \quad \text{(Eq.3)}$$

$$E_{kt}^{(s)} = -\ln(N)^{-1}\sum_{i=1}^{N}\frac{Y_{kit}^{(s)}}{\sum_{i=1}^{N}Y_{kit}^{(s)}}\ln\left(\frac{Y_{kit}^{(s)}}{\sum_{i=1}^{N}Y_{kit}^{(s)}}\right) \quad \text{(Eq.4)}$$

$$w_{kt}^{(s)} = \frac{1-E_{kt}^{(s)}}{\sum_{k=1}^{K}(1-E_{kt}^{(s)})} \quad \text{(Eq.5)}$$

$$E_{ki}^{(t)} = -\ln(T)^{-1}\sum_{t=1}^{T}\frac{Y_{kit}^{(t)}}{\sum_{t=1}^{T}Y_{kit}^{(t)}}\ln\left(\frac{Y_{kit}^{(t)}}{\sum_{t=1}^{T}Y_{kit}^{(t)}}\right) \quad \text{(Eq.6)}$$

$$w_{ki}^{(t)} = \frac{1-E_{ki}^{(t)}}{\sum_{k=1}^{K}(1-E_{ki}^{(t)})} \quad \text{(Eq.7)}$$

$$E_{k}^{(st)} = -\ln(N*T)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\frac{Y_{kit}^{(st)}}{\sum_{i=1}^{N}\sum_{t=1}^{T}Y_{kit}^{(st)}}\ln\left(\frac{Y_{kit}^{(st)}}{\sum_{i=1}^{N}\sum_{t=1}^{T}Y_{kit}^{(st)}}\right) \quad \text{(Eq.8)}$$

$$w_{k}^{(st)} = \frac{1-E_{k}^{(st)}}{\sum_{k=1}^{K}(1-E_{k}^{(st)})} \quad \text{(Eq.9)}$$

$$EA_{it} = \frac{1}{3}\sum_{k=1}^{K}\frac{\sum_{t=1}^{T}w_{kt}^{(s)}Y_{kit}^{(s)}}{T} + \frac{1}{3}\sum_{k=1}^{K}\frac{\sum_{i=1}^{N}w_{ki}^{(t)}Y_{kit}^{(t)}}{N} + \frac{1}{3}\sum_{k=1}^{K}w_{k}^{(st)}Y_{kit}^{(st)} \quad \text{(Eq.10)}$$

where, y_{kit} is the k^{th} indicator's value at t time in i region, N and T represent the number of the space and time units, respectively. $Y_{kit}^{(s)}$, $Y_{kit}^{(t)}$ and $Y_{kit}^{(st)}$ are the normalized values of y_{kit} at the corresponding three dimensions, space, time and spatiotemporal interaction. EA_{it} is the comprehensive measurement values of DED and ULCEHD at t time in i region.

Bayesian graph convolutional neural network (BGCNN) model

The BGCNN framework integrates Bayesian inference within a Graph Convolutional Neural Network (GCNN) (Coley et al., 2019; Zhang et al., 2019a) structure to analyze data characterized by its graph-structured form. This integration allows for the effective handling of uncertainty and the leveraging of graph topology in learning tasks. The BGCNN model (Zhang et al., 2019b) is constructed upon the foundation of GCNNs, which operate on graphs $G = (V, E)$ where V represents the set of vertices and E the set of edges. The graph convolution operation in GCNNs is designed to aggregate information from a node's neighbors, defined as:

$$H^{(l+1)} = \sigma(D^{-\frac{1}{2}}\hat{A}\widehat{D}^{-\frac{1}{2}}H^{(l)}W^{(l)}) \quad \text{(Eq.11)}$$

where $H^{(l+1)}$ is the matrix of activations in the l-th layer, $\hat{A} = A + I_N$ is the adjacency matrix A of the graph with added self-connections I_N , $\widehat{D}$ is the degree matrix of $\hat{A}$, $W^{(l)}$

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is the weight matrix for the l-th layer, and σ denotes a non-linear activation function such as ReLU.

To incorporate Bayesian inference into this framework, we treat the weights $W^{(l)}$ as random variables rather than fixed parameters. We define prior distributions over these weights, typically Gaussian distributions, to encode our prior beliefs about the weights' values:

$$W^{(l)} \sim N(0, \alpha^{-1} I) \quad \text{(Eq.12)}$$

where α is the precision of the prior distribution, influencing the degree of regularization.

The Bayesian inference process aims to compute the posterior distribution over the weights given the data, which is typically intractable. We employ variational inference to approximate this posterior. This involves defining a variational family of distributions $q_\theta(W)$ parameterized by θ and minimizing the Kullback-Leibler (KL) divergence between $q_\theta(W)$ and the true posterior. The optimization objective, or the variational lower bound (ELBO), is given by:

$$\mathcal{L}(\theta) = \mathbb{E}_{q_\theta(W)}[\log p(Y \mid X, W)] - KL(q_\theta(W) \mid\mid p(W)) \quad \text{(Eq.13)}$$

where X and Y denote the input features and target outputs, respectively. The variational posterior $q_\theta(W)$ for each weight matrix was parameterized by mean and variance parameters, which were optimized using stochastic gradient descent. The non-linear activation function used was the ReLU function, and we utilized the Adam optimizer for training the model. This BGCNN performance in this study was assessed using held-out test data based on RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), and R^2 score, ensuring consistency across training and validation phases. These procedures collectively enhance the credibility and replicability of the BGCNN model.

To ensure the robustness and generalizability of the BGCNN model, we conducted systematic model validation, including hyperparameter tuning and overfitting prevention strategies. Hyperparameter optimization was performed using a grid search approach over key parameters such as the number of graph convolutional layers, the dimensionality of hidden units, learning rate, batch size, and prior precision parameter (α). Each combination was evaluated using 5-fold cross-validation on the training set to select the best-performing configuration. The final model employed two hidden layers with 512 and 256 units, respectively, a learning rate of 0.001, and $\alpha = 1.0$, based on empirical performance and computational efficiency.

To prevent overfitting, this study adopted multiple strategies. First, early stopping was applied with a patience of 20 epochs, monitoring the validation loss to halt training once convergence was detected. Second, dropout regularization was conducted on the hidden layers, with dropout rates empirically set 0.5. Third, weight decay (L2 regularization) was added to the loss function to penalize large weights, thus constraining model complexity. Finally, the Bayesian nature of the model itself introduces uncertainty-aware learning, which inherently reduces overfitting by modeling distributions over weights rather than fixed point estimates (Gal and Ghahramani, 2016). To uncover the complex, nonlinear relationship between DED and ULCEHD while considering other factors, we employ Partial Dependence Plots (PDPs) through the BGCNN model. PDPs visualize how DED and ULCEHD influence each other by averaging predictions over various factors, offering a clear view of their interaction. This approach delineates DED's impact on

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ULCEHD, facilitating targeted intervention strategies. By adjusting the DED variable and keeping others constant, PDPs succinctly demonstrate ULCEHD's response, streamlining the analysis of their relationship. Additionally, the BGCNN model adeptly estimates the influence of DED on ULCEHD for individual cities, including those lacking data. This functionality permits an in-depth exploration of the spatial variability in DED's impact on ULCEHD. Utilizing BGCNN's strength in processing graph-structured data—with cities as nodes and their connections as edges—allows for missing value imputation and a detailed analysis of geographical differences in the DED-ULCEHD relationship. This refined approach offers insights into spatial heterogeneity of the influence effect of DED on ULCEHD.

Results

Overall temporal trends of Chinese DED and ULCEHD

DED has shown a notable increase from 2014 to 2023 (*Fig. 1(A)*). In 2014, the mean DED value across cities was 0.312, which rose to 0.385 by 2023, marking a 23.2% increase. The median DED also grew from 0.302 in 2014 to 0.360 in 2023, reflecting an 18.99% rise. The interquartile range (IQR), which measures the middle 50% of the data, expanded significantly from 0.018 in 2014 to 0.041 in 2023, indicating increasing variability in DED across cities. The standard deviation also almost doubled from 0.036 in 2014 to 0.063 in 2023, further underscoring the growing disparities in DED among cities. ULCEHD has also seen significant growth during the same period (*Fig. 1(B)*). The mean ULCEHD value increased from 0.405 in 2014 to 0.497 in 2023, representing a 22.84% increase. The median ULCEHD showed an even larger percentage increase of 25.83%, rising from 0.390 in 2014 to 0.491 in 2023. Unlike DED, the IQR for ULCEHD slightly decreased from 0.155 in 2014 to 0.143 in 2023, suggesting a slight convergence in ULCEHD values across cities. The standard deviation also decreased slightly, from 0.116 in 2014 to 0.101 in 2023, indicating that while the average level of green development has increased, the differences between cities have somewhat lessened over time.

Spatiotemporal distribution of DED and ULCEHD

Spatial pattern of DED and ULCEHD

The spatial distribution of DED across China from 2014 to 2023 shows significant regional disparities (*Fig. 2(A)*). The mean DED values indicate that eastern coastal cities, such as Beijing, Shanghai, and Shenzhen, have consistently higher levels of digital economic development. These cities benefit from better digital infrastructure, more substantial investments in technology, and a higher concentration of tech companies, which contribute to their leading positions. In contrast, the western and northeastern regions, particularly in provinces like Xinjiang and Heilongjiang, exhibit lower DED values, reflecting a slower pace of digital integration and economic transformation. This uneven development pattern underscores the digital divide between the more economically advanced coastal regions and the less developed interior regions.

ULCEHD also exhibits significant spatial variability across China (*Fig. 2(B)*), with some patterns overlapping with those of DED, but with notable differences. The mean ULCEHD values highlight that cities in the southern and eastern parts of China, such as those in Guangdong and Jiangsu provinces, have achieved higher levels of green

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development. These areas benefit from more progressive environmental policies, greater public awareness, and significant investments in green infrastructure. Conversely, the northern and northwestern regions, including provinces like Inner Mongolia and Ningxia, show lower ULCEHD values. The disparity reflects the challenges faced by these regions in balancing economic growth with environmental sustainability, often due to their heavy reliance on traditional, resource-intensive industries.

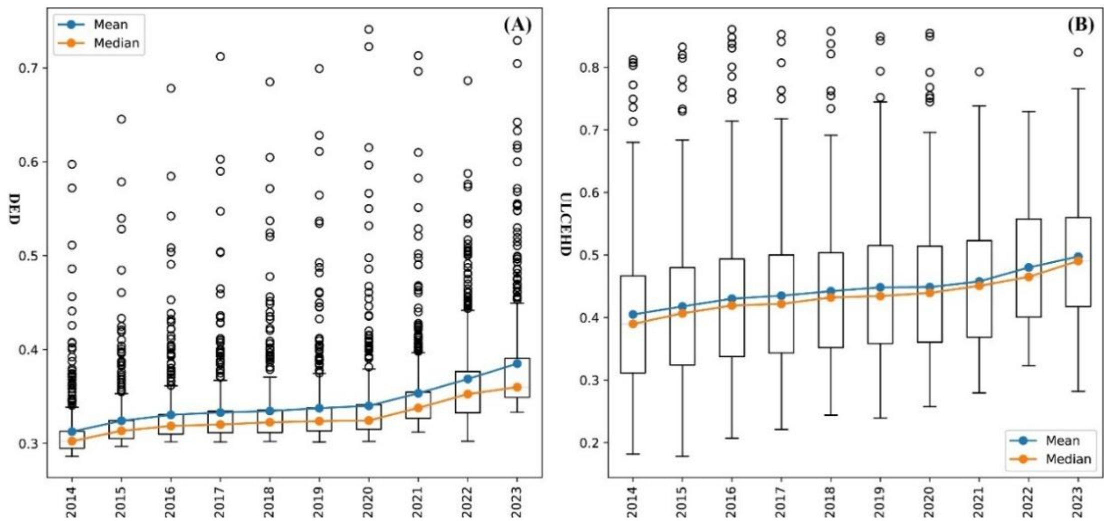

Figure 1. *(A) Boxplot of Digital Economy Development (DED) across Chinese prefecture-level regions from 2014 to 2023, with the blue and orange lines indicating the annual mean and median values, respectively. (B) Boxplot of Urban Low-Carbon Ecological High-Quality Development (ULCEHD) over the same period*

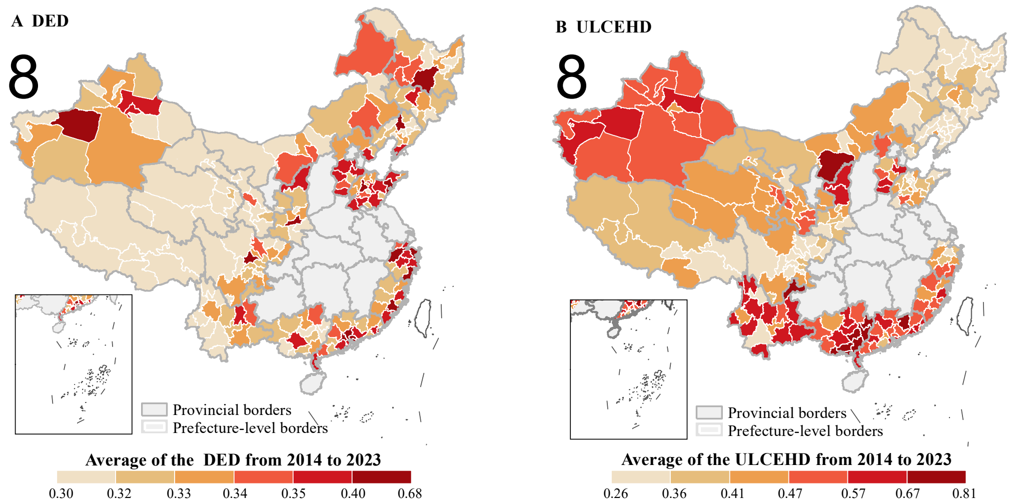

Figure 2. *(A) Spatial distribution of the average Digital Economy Development (DED) index across Chinese prefecture-level regions from 2014 to 2023. (B) Spatial distribution of the average Urban Low-Carbon Ecological High-Quality Development (ULCEHD) index over the same period. The color gradient indicates the level of development, with darker shades representing higher values*

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Local trends of DED and ULCEHD

The annual changes in DED from 2014 to 2023 (*Fig. 3(A)*) reveals significant regional variation in growth patterns across China. Notably, the western and northern regions, particularly areas such as Xinjiang, Inner Mongolia, and parts of Heilongjiang, demonstrate the most substantial annual increases in DED, with some regions experiencing growth rates as high as 0.0253 per year. This indicates that these historically less developed areas are beginning to catch up with the digital advancements seen in the more economically developed eastern regions. However, the result also highlights that some parts of the central and southern regions have relatively lower annual growth rates, suggesting that these areas might be reaching saturation in their DED or facing barriers to further growth.

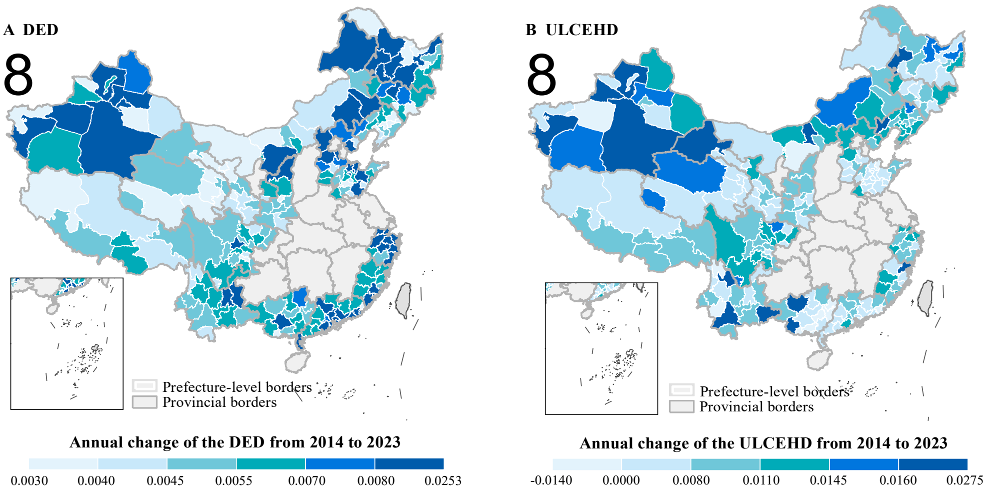

Figure 3. *(A) Spatial distribution of the average annual change in Digital Economy Development (DED) across Chinese prefecture-level regions from 2014 to 2023. (B) Spatial distribution of the average annual change in Urban Low-Carbon Ecological High-Quality Development (ULCEHD) over the same period*

The annual change of ULCEHD from 2014 to 2023 (*Fig. 3(B)*) shows a complex pattern of growth that differs from the trends seen in DED. The most significant increases in ULCEHD are observed in the northern and northwestern regions, particularly in areas such as Inner Mongolia and Xinjiang, where annual growth rates reach up to 0.0275. This pattern suggests a strong regional emphasis on improving green infrastructure and implementing sustainable urban practices, likely driven by local policies and environmental pressures. On the other hand, some regions in the eastern and southern parts of China show negative or minimal growth in ULCEHD, indicating potential challenges in balancing economic growth with environmental sustainability or possible declines in green development due to urban expansion.

Driving effect of DED on ULCEHD

Preliminary analysis

To interrogate the interplay between DED and ULCEHD, the line regression analysis was initially employed, as illustrated in *Fig. 4*. This fundamental statistical methodology reveals a data point dispersion suggestive of a potential positive correlation between DED

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and ULCEHD. A superimposed linear regression line reinforces this empirical observation. The associated regression equation corroborates a positive, albeit weak, association between DED and ULCEHD, as substantiated by a Pearson's correlation coefficient of 0.2131 ($p<0.05$).

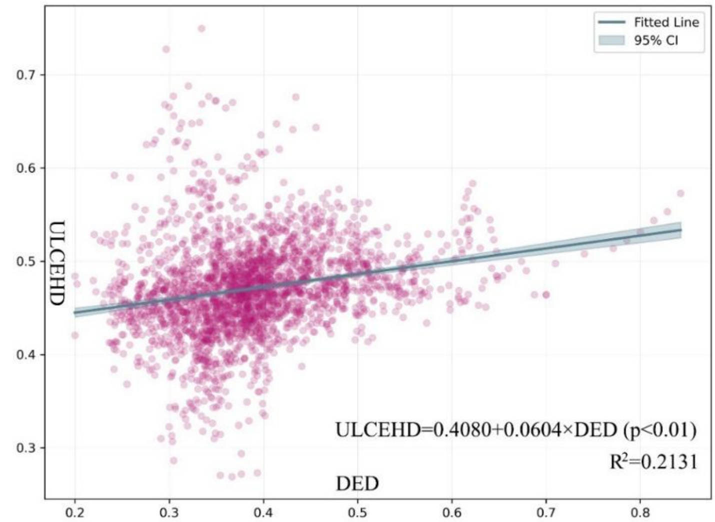

Figure 4. *Scatter plot showing the linear relationship between Digital Economy Development (DED) and Urban Low-Carbon Ecological High-Quality Development (ULCEHD) across Chinese prefecture-level regions from 2014 to 2023. The fitted regression line (blue) and the 95% confidence interval (shaded area) indicate a statistically significant positive correlation between the two variables ($p < 0.01$), although with moderate explanatory power ($R^2 = 0.2131$)*

Nonlinear effect of DED on ULCEHD

The BGCNN demonstrates strong predictive performance, as reflected in the high R^2 values for both the training set (0.9734) and test set (0.8358), indicating that the majority of variance in ULCEHD can be explained by the selected predictors. The low values of RMSE (0.0083 for training and 0.0191 for test) and MAE (0.0054 for training and 0.0136 for test) further confirm the BGCNN's accuracy and generalization ability. To assess the robustness of the model, a subsample-based validation was conducted by randomly selecting 80% of the original dataset and re-estimating the model. The results remained highly consistent with the baseline estimates, with the training R^2 reaching 0.9723 and test R^2 at 0.8322, indicating strong explanatory power. The prediction errors were also within an acceptable range, with RMSE values of 0.0086 (training) and 0.0196 (test), and MAE values of 0.0055 and 0.0137, respectively. The close alignment between the subsample and full-sample results confirms the BGCNN's stability and supports the reliability of the main findings (*Table 4*).

The evaluation of the feature importance rankings and the nonlinear effects as estimated by the BGCNN model provides a comprehensive understanding of the accelerating effect of DED on ULCEHD. The feature importance rankings reveal that URB and DED hold the most significant influence on ULCEHD with an importance score of 19.46% and 19.03%. ECO and GOV are also substantial contributors to ULCEHD, with importance scores of 16.69% and 15.94%, respectively. FIN and OPN complete the list with respective scores of 15.71% and 13.17%, indicating their consequential but lesser impact compared to other factors.

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***Table 4.** Results of robustness checks comparing model performance between full sample and 80% random subsample*

Indicator	Full-Sample	80% Subsample
R^2 (Train)	0.9734	0.9723
R^2 (Test)	0.8358	0.8322
RMSE (Train)	0.0083	0.0086
RMSE (Test)	0.0191	0.0196
MAE (Train)	0.0054	0.0055
MAE (Test)	0.0136	0.0137

The nonlinear dose-response curves estimated by the BGCNN model further elucidate the intricate nonlinear effects of various factors on ULCEHD (*Fig. 5*). The curve corresponding to DED vs. ULCEHD delineates "S-shaped" trajectory, indicating an initial phase of gradual ULCEHD enhancement with early increments in DED. This phase is characterized by a slow yet steady increase, with ULCEHD improving by an estimated 0.02 units for each 0.10 increase in DED. Progressing beyond a DED level of 0.375, the curve steepens, signifying a more pronounced impact on ULCEHD with further advancements in DED. This steepening is quantitatively marked by a 0.20 rise in ULCEHD per 0.10 increase in DED, up to a DED level of 0.45, after which the curve plateaus, suggesting a saturation point in the effectiveness of DED on ULCEHD. The relationships between ULCEHD and the other variables, although diverse in their function forms, emphasize the heterogeneous and nonlinear nature of their impacts. Notably, the relationship between FIN and ULCEHD mirrors the pattern observed in DED vs. ULCEHD, reinforcing the primacy of urbanization in driving green development. Both ECO and URB show a positive linear relationship with ULCEHD, and the effect of GOV on ULCEHD weakens as GOV increases. Conversely, OPN vs. ULCEHD presents an initial decline in ULCEHD with increased openness.

Spatial heterogeneity of influencing effect of DED on ULCEHD

The spatial distribution of the driving effect of DED on ULCEHD at the prefectural level across China, as depicted in *Fig. 6*, reveals considerable regional heterogeneity. The result, estimated from the BGCNN model, highlights the intricate relationship between digital economic growth and urban sustainability outcomes. Notably, the map identifies several regions where the enhancement of DED has a particularly pronounced impact on ULCEHD, represented by darker hues. These regions, which include parts of central China (such as Hunan and Hubei provinces), southwestern China (including Sichuan and Yunnan provinces), and northeastern China (notably Heilongjiang and Jilin provinces), demonstrate a high responsiveness to digital economic advancements. In these areas, a 0.10 increase of DED in 2023 correlates with substantial ULCEHD improvements, ranging from 0.27 to 0.31. The strong impact observed in these regions may be attributed to a combination of supportive economic structures, proactive governance, and well-developed digital infrastructures, which together enhance the efficacy of digital initiatives in driving sustainable urban development.

The observed spatial heterogeneity in the driving effects of DED on ULCEHD can be attributed to several underlying mechanisms. First, regions are situated at different stages of digital development: while less developed regions may be in a phase of digital acceleration, advanced regions may already face diminishing marginal ecological returns

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due to digital saturation. Second, regional differences in absorptive capacity—including technological infrastructure, human capital, and institutional quality—affect how effectively digital inputs are transformed into ecological outcomes. In regions with stronger innovation ecosystems and environmental governance, DED is more likely to be channeled toward sustainable applications. Third, local variations in governance capacity and the integration between digital technologies and environmental policy tools (e.g., smart monitoring, green financing platforms) further mediate the impact. Finally, in highly digitalized regions, path dependence and technological lock-ins may constrain the room for additional ecological gains, while also raising issues of digital externalities such as energy-intensive data operations.

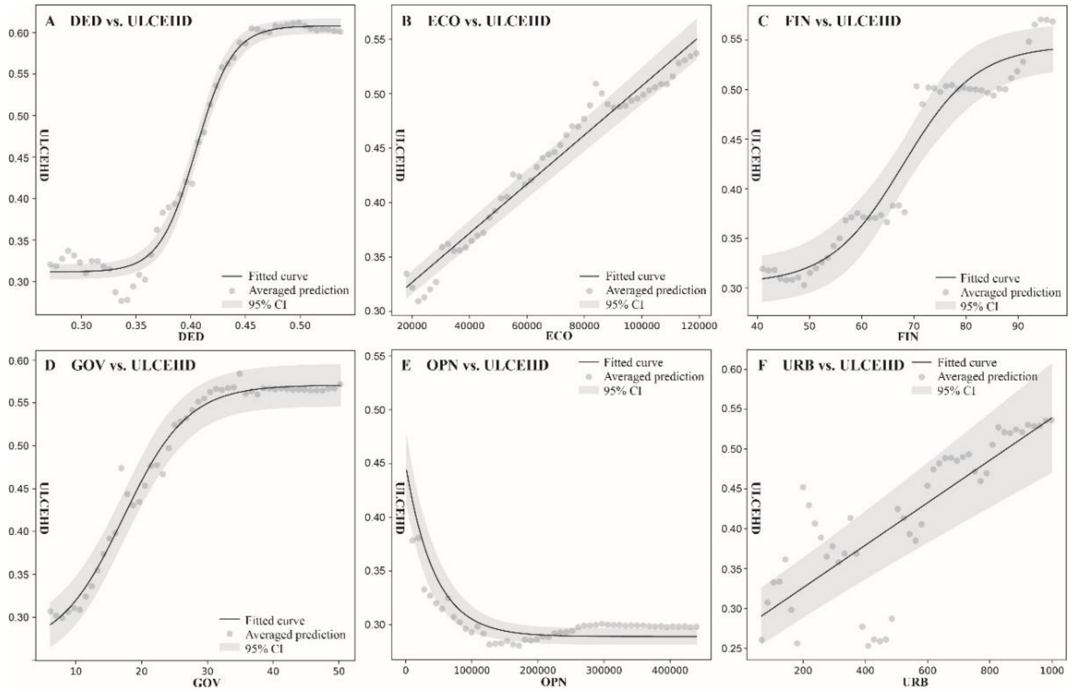

__Figure 5.__ Bayesian Graph Convolutional Neural Network (BGCNN) estimated dose–response curves between key predictors and Urban Low-Carbon Ecological High-Quality Development (ULCEHD) across Chinese prefecture-level cities.(A) Digital Economy Development (DED) shows an S-shaped nonlinear relationship with ULCEHD, indicating threshold effects.(B) Economic development (ECO) demonstrates a nearly linear positive influence.(C) Financial development (FIN) exhibits a nonlinear pattern with accelerating returns after a critical level.(D) Government intervention (GOV) presents a plateauing effect beyond a certain point.(E) Openness (OPN) shows limited marginal effects.(F) Urbanization level (URB) maintains a steady positive association. The shaded areas represent 95% confidence intervals and dots denote average model predictions under varying covariate values

Prediction of DED in 2030

The prediction of DED in 2030, based on the observed local trends from 2014 to 2023, suggests a transformative shift in the spatial distribution of digital economic activities across China, marking a departure from the patterns seen in 2023 (*Fig. 7(B)*). During the baseline year of 2023 (*Fig. 7(A)*), DED was predominantly concentrated in a few key regions—most notably Xinjiang, Heilongjiang, and select areas of central China such as

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Hubei, Sichuan, and Guizhou. These regions had established themselves as digital economic strongholds, benefiting from early investments in digital infrastructure, government support, and a growing digital workforce. However, the projection for 2030 indicates that DED will no longer be confined to these traditional hubs but is expected to diffuse more evenly across the nation. This broadening of digital economic activity suggests that regions like Xinjiang and Heilongjiang will not only maintain their leadership but also extend their influence to surrounding areas, amplifying their role as regional digital powerhouses. Meanwhile, the central and eastern provinces of Henan, Anhui, and Jiangsu are predicted to experience substantial growth in DED. These regions, traditionally more reliant on manufacturing and agriculture, are poised to become new centers of digital innovation and economic dynamism, signaling a more balanced and inclusive digital economy across China by 2030.

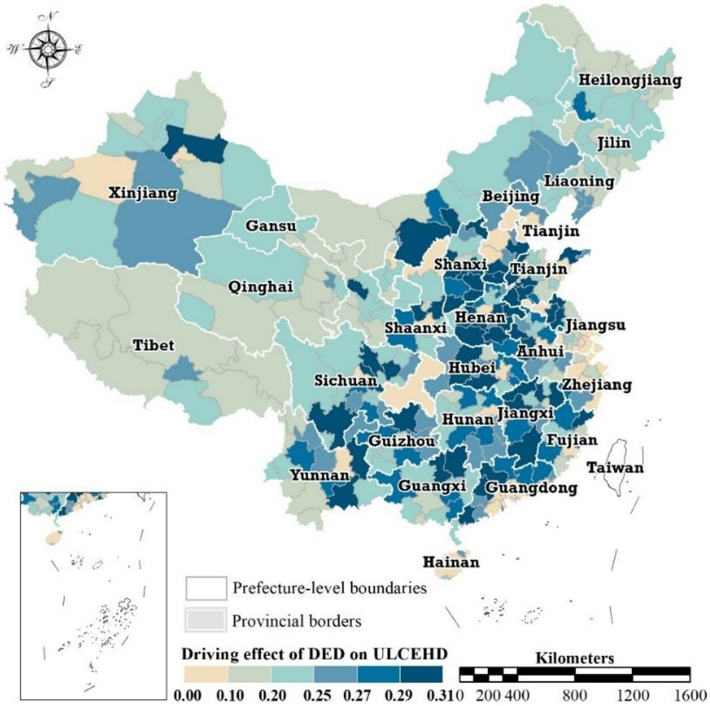

Figure 6. *Spatial distribution of the estimated marginal effect of Digital Economy Development (DED) on Urban Low-Carbon Ecological High-Quality Development (ULCEHD) when DED increases by 0.10 from its 2023 level, based on BGCNN model predictions at the prefecture-level. All other factors are held constant. Darker areas indicate stronger positive effects of DED on ULCEHD*

This anticipated expansion indicates a move towards a more balanced distribution of DED across China by 2030. *Figure 7* highlights emerging digital hubs and suggest that regions poised for rapid growth will need to focus on improving digital infrastructure, workforce skills, and governance to fully leverage these opportunities. At the same time, areas currently lagging may require targeted policies to ensure they are not left behind in this digital transformation. These predictions provide valuable insights for regional planning and policy-making, helping to guide efforts to ensure that digital economic growth benefits all regions of China equitably.

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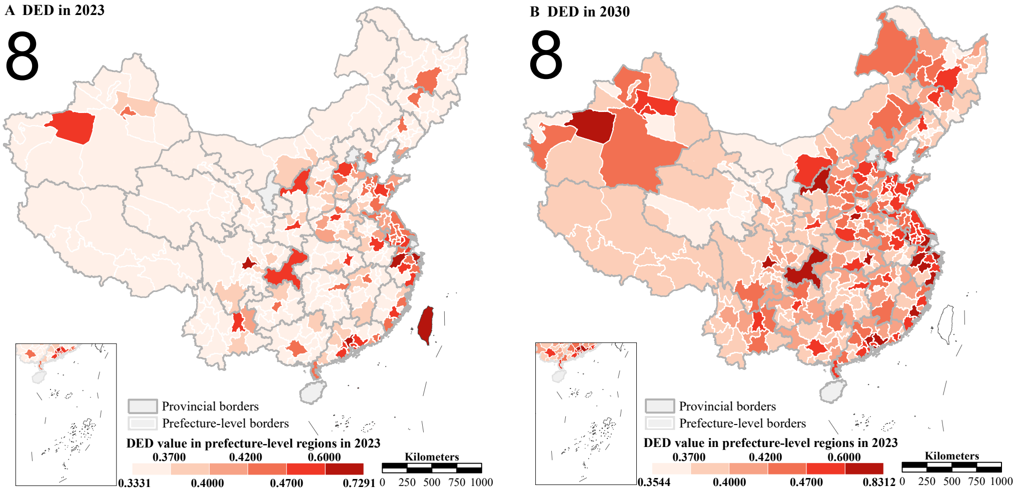

Figure 7. *(A) Spatial distribution of Digital Economy Development (DED) across Chinese prefecture-level cities in 2023. (B) Predicted DED values in 2030 based on local historical trends from 2014 to 2023, using extrapolated temporal trajectories*

Prediction of ULCEHD in 2030 driven by the increased DED in 2030

The projection of ULCEHD in 2030 was conducted in two stages. First, each region's DED value was forecasted to 2030 based on its historical spatiotemporal trajectory. Second, the forecasted DED values were input into the dose-response relationship derived from the BGCNN model to estimate the incremental changes in ULCEHD. This approach assumes a continuation of existing trends (business-as-usual) without considering exogenous shocks or alternative policy scenarios.

The ULCEHD in 2030 (*Fig. 8(B)*) driven by the increased DED was estimated by the BGCNN model. The result presents a significant shift in the spatial distribution of urban sustainability across China. As depicted in *Figure 7*, there is a noticeable improvement in ULCEHD across various regions between 2023 and 2030. In 2023, regions with higher levels of ULCEHD were primarily concentrated in Xinjiang, parts of northeastern China such as Heilongjiang, and some central provinces including Hunan and Guizhou. However, the projection for 2030 indicates not only the persistence of high ULCEHD levels in these areas but also an expansion of significant ULCEHD improvements into other regions.

By 2030, as the DED intensifies, its influence on ULCEHD becomes more widespread, particularly in regions that were previously lagging. Provinces in central and eastern China, such as Henan, Anhui, and Jiangsu, exhibit substantial increases in ULCEHD, driven by the growth of their DED. This spatial broadening of ULCEHD highlights the critical role of DED as a catalyst for urban sustainability, suggesting that regions with robust digital economic growth are better positioned to achieve significant green development outcomes. The diffusion of ULCEHD improvements across a broader spectrum of regions underscores a more balanced and inclusive trajectory of urban green development, reflecting the effectiveness of targeted policies and investments in digital infrastructure to foster sustainability across China's diverse urban landscape.

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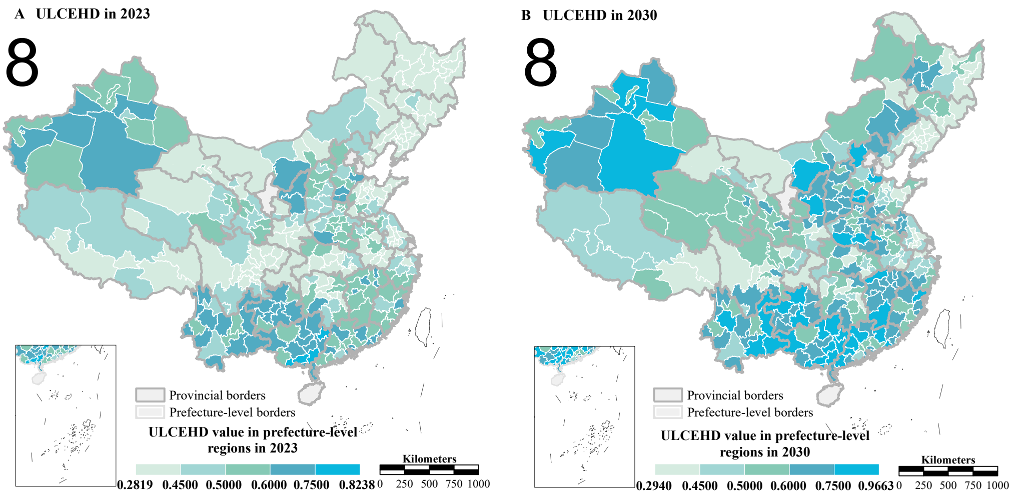

Figure 8. *(A) Spatial distribution of Urban Low-Carbon Ecological High-Quality Development (ULCEHD) across Chinese prefecture-level cities in 2023(B) Predicted ULCEHD in 2030, based on projected increases in Digital Economy Development (DED) under the business-as-usual (BAU) scenario*

Discussion

This study has proposed STEWM to quantitatively measure DED and ULCEHD at prefecture-level scale in China from 2014 to 2023. Subsequently, the overall trend, the steady spatial pattern and local trend of DED and ULCEHD were explored. The BGCNN model, a state-of-the-art machine learning method, was employed to investigate the nonlinear and heterogeneous accelerating effect of DED on ULCEHD at prefecture-level scale in China. Finally, this paper predicted the DED in 2030 according to the local trend from 2014 to 2023, and the projected ULCEHD in 2030 driven by increased DED was estimated by the BGCNN model.

The spatiotemporal trends in DED and ULCEHD from 2014 to 2023 reflect the ongoing interplay between economic modernization and sustainability in China. The concentration of high DED levels in eastern coastal cities highlights a persistent digital divide, consistent with Fan et al. (2024) who observed stronger digital economic growth in regions with better infrastructure and technological investment.

The S-shaped dose–response curve between DED and ULCEHD suggests that initial digital investments yield modest ecological benefits, which then accelerate after surpassing a critical development threshold. This finding aligns with Zhong et al. (2022), who reported that digital economy advancement reduces carbon intensity, particularly in resource-intensive regions, through improved energy structures and green innovation. However, the observed plateau at higher DED levels indicates diminishing returns, echoing Huo et al. (2022), who emphasized the spatial spillover limits of digitalization and the critical role of supportive regional policies. These results highlight the need for a balanced approach that integrates digital expansion with regulatory and infrastructural support to sustain urban ecological development across regions.

The spatial heterogeneity in the impact of DED on ULCEHD carries important implications for regional policy-making in China. In regions where the relationship is stronger—such as central, southwestern, and northeastern China—policymakers should amplify these synergies through targeted investments in digital infrastructure, innovation

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ecosystems, and sustainable urban planning. These areas typically benefit from a favorable combination of digital readiness and supportive governance, as noted by Liu et al. (2023). Conversely, in regions with weaker DED–ULCEHD linkages, such as the North China Plain and parts of the eastern coast, interventions should focus on overcoming integration barriers by enhancing digital literacy, strengthening institutional capacity, and addressing environmental constraints. This aligns with Ma and Zhu (2022), who emphasize the importance of embedding digital technologies into traditional industries to drive high-quality green development. A differentiated policy approach based on local digital maturity and institutional conditions can help ensure that the benefits of digitalization are equitably distributed, contributing to balanced and sustainable regional development. Building on the observed spatial heterogeneity, more tailored policy recommendations are necessary to guide digital-ecological coordination across different regional contexts. In digitally advanced cities—such as those in the eastern coastal region—policies should focus on improving energy efficiency in digital infrastructure (e.g., promoting green data centers), supporting platform accountability, and enhancing the quality of digital services for sustainability. In contrast, cities with low or moderate levels of DED, particularly in central and western China, would benefit from increased investment in basic digital infrastructure, vocational digital training programs, and policy incentives to guide digital applications in green manufacturing, public service delivery, and urban planning. For resource-dependent regions, integrating digital tools into environmental monitoring, cleaner production, and ecological restoration may be particularly impactful. Such differentiated policy strategies can help ensure that digital transformation accelerates rather than fragments China's green development agenda.

These findings also provide empirical support for China's broader national strategies, including the Digital China Initiative and the Dual Carbon Goals (carbon peaking by 2030 and carbon neutrality by 2060). As digital transformation becomes a key driver of industrial upgrading and environmental modernization, leveraging its potential in a regionally adaptive way will be crucial for aligning technological progress with ecological objectives. The differentiated impact of DED observed in this study highlights the need for coordinated policy frameworks that integrate digital infrastructure investment with climate action and green innovation, thereby advancing both economic competitiveness and environmental sustainability at the national level.

While the findings underscore the positive role of DED in promoting ULCEHD, potential unintended consequences of digital economy expansion should also be acknowledged. The rapid growth of data centers, cloud computing, and AI-driven platforms may lead to increased energy consumption, potentially offsetting some ecological gains if not managed properly. Additionally, the spatially uneven distribution of digital resources and capacities could exacerbate regional inequalities, with digitally lagging regions missing out on the green dividends of digitalization. There is also a risk of digital lock-in or over-reliance on capital-intensive technologies that may marginalize smaller enterprises or exclude vulnerable populations. Addressing these challenges requires a balanced development model that integrates digital economy planning with energy transition goals, social inclusion policies, and long-term ecological safeguards.

One limitation of this study lies in the spatial resolution. while the prefectural-level analysis provides useful insights, it may overlook important intra-city variations and rural–urban gradients Future research could adopt finer spatial units, such as counties or districts, to investigate how neighborhood-level digital infrastructure and governance influence ecological outcomes, or to examine disparities within large metropolitan areas.

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Additionally, although the 2014–2023 time frame captures recent developments, extending the temporal horizon would allow for the exploration of long-term lagged effects, policy transitions (e.g., before and after the "Digital China" strategy), and structural turning points in the DED–ULCEHD relationship. Incorporating such extensions would enhance understanding of both the temporal dynamics and micro-spatial mechanisms through which digitalization affects sustainable urban development.

Conclusions

Firstly, this study finds that DED significantly promotes ULCEHD in China, with a nonlinear, S-shaped relationship and marked spatial heterogeneity. The impact is stronger in regions with moderate DED levels and appropriate institutional and infrastructure conditions. Secondly, these uneven regional effects underscore the importance of differentiated policy strategies to align digital development with sustainability goals, particularly within the framework of China's national digital transformation and carbon neutrality agendas. Thirdly, projections for 2030 based on local DED trends and the BGCNN model suggest continued growth in DED and its positive ecological impact, with a more balanced spatial distribution and stronger digital–ecological synergy in currently underdeveloped regions.

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