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Multidimensional spatial inequality in China and its relationship with economic growth

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Spatial inequality erodes social cohesion and political stability, impacting global sustainable development and human well-being. This study examines spatial inequality in China across economic, social, environmental, infrastructural, and innovation dimensions, exploring how these inequalities evolve with economic development. Drawing on the Sustainable Development Goals and Chinese planning goals, we selected 13 indicators pertinent to human well-being. We employed the population-weighted coefficient of variation, Gini coefficient, and Moran's I to assess spatial inequalities and analyzed their relationship with economic growth. The findings reveal that China currently exhibits the highest spatial inequality in innovation and the lowest in the social dimension. Since 1990, most indicators have trended towards decreasing spatial inequality, except for unemployment rates and carbon emissions, which have increased. The economic and innovation gap between the eastern coastal regions and the central and western regions has widened, whereas disparities in housing, healthcare, roads, and digitalization have narrowed. China's experience demonstrates that Williamson's inverted U-shaped hypothesis extends beyond the economic domain to encompass education, healthcare, infrastructure, and digitalization, providing policy insights for addressing regional inequalities in China in the post-pandemic era.

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Introduction

Spatial inequality, a principal dimension of social inequality, undermines social cohesion and political stability, posing significant barriers to global sustainable development and human well-being (Kanbur and Venables, 2005). Despite international efforts to alleviate poverty in underdeveloped regions, stark disparities persist between the wealthiest and poorest nations and regions. For instance, the average income in North America is sixteen times that of sub-Saharan Africa (Nations, 2020). Additionally, regional inequalities within countries remain prevalent (Eva et al., 2022; Weiss et al., 2018), and in many OECD countries, disparities in GDP per capita, disposable income, safety, and air pollution are widening (OECD, 2016). In this context, the United Nations Sustainable Development Goal 10 aims to reduce inequalities within and among countries (Cheng et al., 2021).

Regional inequality is a complex social phenomenon, manifesting not only in economic development and income levels but also in access to education, healthcare, housing, infrastructure, and digital services (Hu et al., 2023; Shao and Kostka, 2023; Zhou et al., 2022). Furthermore, it includes environmental justice issues such as air pollution, carbon emissions, and access to green spaces (Chancel, 2022; Liu et al., 2022; Wu et al., 2023). Regrettably, the outbreak of the COVID-19 pandemic has further exacerbated inequalities across multiple dimensions both between and within countries (Rothwell et al., 2024). We aim to pursue a more equitable world where individuals have equal opportunities, irrespective of their birthplace (Stiglitz, 2012). Reducing regional disparities is a critical policy objective for governments worldwide, and understanding spatial inequality and its evolution has been a major focus of academic research.

Scholars predominantly focus on spatial inequality in the realms of economy and income. Williamson (1965) articulated a seminal hypothesis suggesting that regional inequality and economic growth may exhibit an inverted U-shaped relationship. This posits that regional economic disparities initially widen and subsequently narrow as economic development progresses. Grounded in the “inverted U-shaped hypothesis” of Kuznets (1955), Williamson’s theory, supported by empirical data, illustrates that spatial polarization of economic activity is an inevitable phase during the nascent stages of national economic development. However, as economic development reaches maturity, the regional economic inequality diminishes. This aligns with Solow’s classic “convergence hypothesis,” which postulates that, under identical economic conditions, poorer countries experience faster per capita growth compared to wealthier nations (Solow, 1956).

However, Williamson’s theory has been the subject of considerable debate. Some studies lend support to this hypothesis. For instance, analysis of data from 20 OECD countries between 1960 and 1985 revealed a negative correlation between the average growth rate of per capita GDP and the level of economic development (Barro et al., 1991). An empirical examination of 56 countries from 1980 to 2009 also strongly supports the existence of an inverted-U relationship, although spatial inequalities increase again at very high levels of economic development (Lessmann, 2014). Case studies in the UK, France, Italy, and Spain further confirm this inverted U-shaped pattern (Barrios and Strobl, 2009; Diez-Minguela et al., 2020; Tirado et al., 2016). Conversely, numerous scholars have challenged the scientific validity of the “inverted U-shaped hypothesis”. For example, (Baumol, 1986) analyzed the per capita income growth rates of 22 countries from 1870 to 1979 and demonstrated that poorer countries did not converge with richer ones; instead, they exhibited the slowest growth rates. Furthermore, regional inequality in the ASEAN region and economic development

follows an inverted N-shaped relationship (Chen and Zhang, 2023). Other research indicates that regional inequality increases at very high levels of GDP per capita (Breinlich et al., 2014).

Over the past 40 years, China has undergone rapid economic development, yet spatial inequality remains a significant issue (Huang and Wei, 2019; Zhou and Zheng, 2024). Scholars have systematically investigated economic disparities and their underlying mechanisms using measures such as the coefficient of variation, Gini coefficient, and Theil index across regional, provincial, and urban scales (He et al., 2017; Li and Wei, 2010). China’s regional inequality has gradually shifted from the gap between the eastern coastal areas and the western inland regions to an increasing disparity between the north and the south (Liang et al., 2021). Studies have shown that factors such as geography, transportation, globalization, urbanization, technological advancement, migration, and investment have varying degrees of influence on regional economic disparities (Fujita and Hu, 2001; Huang and Wei, 2016; Kanbur and Zhang, 2005; Zhang and Zou, 2012). Research has also explored the roles of agglomeration economies, knowledge spillovers, and path dependence in regional development (Fleisher et al., 2010; Lim, 2017). A key focus has been the impact of regional policies on economic disparities across different periods in China (Dunford and Li, 2010). For instance, the Western Development Strategy has significantly promoted infrastructure and industrial development in the lagging western regions (Peng and Chen, 2016). Beyond economic disparities, research highlights significant and worsening inequalities in China’s housing market (Zhao et al., 2021). Although digital inequality remains pronounced, spatial disparities are decreasing (Liu et al., 2017). While nine-year compulsory education is widespread, notable spatial inequalities persist in secondary education (Wu and Kc, 2023). In healthcare, high-quality medical resources are predominantly concentrated in major cities, exacerbating inequalities (Liu et al., 2020). Spatial disparities in carbon intensity and car ownership are showing signs of decline (Duan et al., 2024; Wang et al., 2019). A growing disparity in energy burdens has been observed (Wang et al., 2023), and as China’s innovation capabilities enhance, the pronounced effects of innovation agglomeration continue (Xu et al., 2022).

Despite previous research, there are still some gaps that need to be filled. Previous research on spatial inequality has predominantly focused on economic disparities, with less emphasis on dimensions critical to human welfare such as society, environment, infrastructure, and innovation. Comparative analyses across these various dimensions within China are notably scarce. Discussion of Williamson’s inverted “U” theory has largely been confined to the economic domain, with case studies focused on developed economies. Questions about whether spatial inequalities in other dimensions conform to this hypothesis, and its applicability in China, remain empirically unaddressed. Accordingly, this study seeks to explore the following questions: What is the extent of spatial inequality in China across economic, social, environmental, infrastructure, and innovation dimensions? How have these disparities evolved over the past three decades? Has rapid economic growth in China narrowed regional disparities? Does the relationship between China’s economic growth and spatial inequalities across different developmental dimensions follow an inverted U-shaped pattern?

Drawing on the Sustainable Development Goals (SDGs) and Chinese planning goals, we selected 13 indicators closely associated with human welfare across five dimensions: economy, society, environment, infrastructure, and innovation. We employed population-weighted coefficients of variation, Gini coefficients, and Moran’s I to assess the spatial inequality and

clustering of each indicator at the provincial level in China. Subsequently, we constructed regression models to explore the evolving relationship between spatial inequalities in these dimensions and economic growth. Finally, we propose some policy implications.

The contributions of this study are threefold: Firstly, while previous research on spatial inequality has often focused on isolated aspects of economic or social dimensions, we integrate multiple dimensions—economy, society, environment, infrastructure, and innovation—that are closely linked to human well-being. This comprehensive approach allows for a comparative analysis of spatial inequalities across these dimensions in China over the past three decades. Secondly, explorations of Williamson’s inverted U-shaped hypothesis have predominantly been confined to economic contexts and developed economies. We test the applicability of this hypothesis across various dimensions—economic, social, environmental, infrastructural, and innovative—in the Chinese context. Thirdly, by combining traditional spatial inequality indices with spatial autocorrelation indices, we extend the scope of Williamson’s hypothesis. Our findings reveal an inverted U-shaped relationship between economic growth and spatial inequalities in income, education, healthcare, infrastructure, and digitalization in China. Rapid economic growth appears to mitigate spatial inequalities across most indicators. These conclusions offer valuable insights for policymakers aiming to promote regional balanced development and reduce regional inequalities in China, particularly in the post-pandemic era.

Data and methods

Indicator selection and data sources. We selected 13 indicators across five key dimensions—economy, society, environment, infrastructure, and innovation—that are essential for assessing multidimensional inequalities in regional development across China. These indicators are detailed in Fig. 1. All chosen indicators align with those outlined in the SDGs (see Table 1). Each indicator is also featured in China’s governmental documents, with nine of them specifically highlighted in the country’s most critical development framework for the next decade—the 14th Five-Year Plan (2021–2025) for National Economic and Social Development and the Long-Range Objectives Through the Year 2035 (China’s 2035 objectives)¹. These nine indicators include GDP per capita, disposable income per capita, rate of high school graduates and above, density of physicians, unemployment rate, PM_{2.5} concentration, carbon emissions per capita, granted patents per capita, and R&D expenditure per capita. Table 1 provides descriptive statistics for these indicators and maps their alignment with the SDG metrics.

Our study encompasses 31 provincial units in China, excluding Hong Kong, Macau, and Taiwan, and covers the period from 1990 to 2021 (Fig. 2). The majority of data were derived from several Chinese statistical annuals, including the China Statistical Yearbook, Population and Employment Statistical Yearbook, China Census Yearbook, and China Science and Technology Statistical Yearbook. Internet penetration rates were sourced from the China Internet Development Report², carbon emissions from

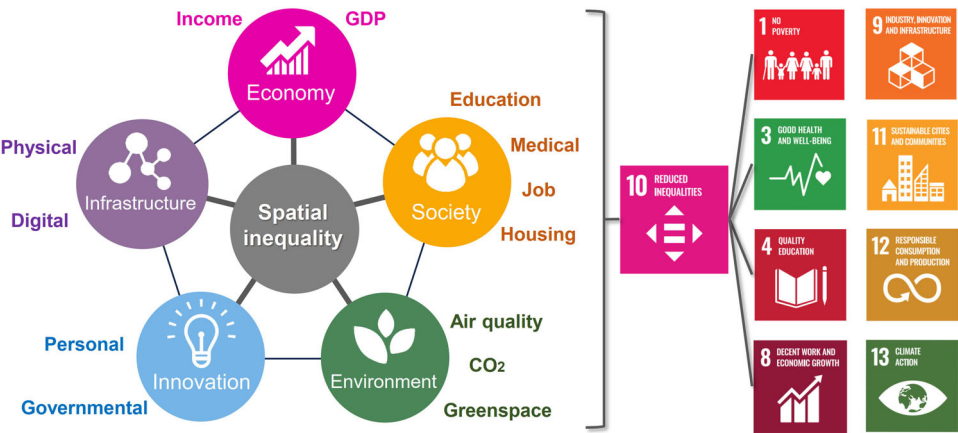


Fig. 1 Assessment indicators of multidimensional inequality in China link the Sustainable Development Goals (SDGs).

Table 1 Statistical descriptions of indicators for assessing inequalities among Chinese provinces.								
Dimension	Indicator	Corresponding SDG Indicator	Symbol	Unit	Mean	Std.Dev.	Min	Max
Economy	GDP per capita	SDG 8.1.1	GDP	10,000 yuan	2.65	2.83	0.08	13.40
	Disposable income per capita	SDG 1.1	DI	10,000 yuan	1.58	1.24	0.21	7.80
Society	Rate of high school graduates and above	SDG 4.1.2	HG	%	21.39	11.43	0.41	69.87
	Density of physicians	SDG 3.c.1	DP	per 10,000 people	60.63	26.45	22.96	159.01
	Unemployment rate	SDG 8.5.2	UR	%	3.31	0.93	0.30	7.40
Environment	Living space per capita	SDG 11.1.1	LS	m ²	30.62	8.05	13.56	57.15
	PM _{2.5} concentration	SDG 11.6.2	PM2.5	µg/m ³	46.89	16.41	3.19	96.84
	Carbon emission per capita	SDG 13.2.2	CE	t	5.05	4.35	0.27	34.66
	Urban green space per capita	SDG 11.7.1	GS	m ²	5.11	2.83	0.69	18.76
Infrastructure	Road density	SDG 11.2.1	ROD	km/km ²	0.72	0.51	0.02	2.44
	Internet penetration rate	SDG 9.c.1	IPR	%	33.57	23.88	0.48	86.00
Innovation	Granted patents per capita	SDG 9.5.2	GP	per 10,000 people	5.13	10.68	0.01	90.81
	R&D expenditure per capita	SDG 9.5.1	R&D	yuan	533.47	1122.41	4.78	12011.42



Fig. 2 China's provincial units and regional development strategy zones.

the MEIC database³, and PM_{2.5} concentrations from Washington University in St. Louis⁴. To account for inflation and enable temporal comparisons, GDP was computed using constant 1990 prices. Due to the lack of official statistics or consistent monitoring, data for certain indicators—including living space per capita, PM_{2.5} concentration, urban green space per capita, road density, and internet penetration rate—were either unavailable or unreliable prior to 2000. Consequently, only data from 2000 to 2021 were used for these indicators.

Methods

Spatial inequality measurement. Common quantitative measures of spatial inequality include the Coefficient of Variation (CV), Gini Coefficient, Theil Index, Lorenz Curve, and Atkinson Index (Portnov and Felsenstein, 2005; Roy et al., 2024a). Each method has its own strengths and limitations: the Gini Coefficient is well-suited for in-depth analysis where understanding underlying mechanisms is essential, though it is sensitive to outliers; the Theil Index is advantageous for multi-scale spatial analysis as it can be decomposed into within-region and between-region inequalities, but it is also sensitive to extreme values; the Coefficient of Variation is straightforward and facilitates comparisons across different datasets; the Lorenz Curve offers an intuitive graphical representation, although it is relatively challenging to quantify; and the Atkinson Index, while less commonly used, captures the sensitivity of different social groups to inequality,

depending on the choice of the inequality aversion parameter. Since this study does not involve multi-scale comparisons nor considers social aversion to inequality, we selected the CV and Gini Coefficient as our primary methods. Additionally, we extended the CV by incorporating population weighting. To account for spatial effects, we also introduced Moran's I (Roy et al., 2024b).

Population weighted coefficient of variation. The standard CV treats each analysis unit equally, regardless of its population size. This approach can be misleading, particularly if smaller regions disproportionately affect the overall variability. In contrast, the population-weighted coefficient of variation (WCV) adjusts for the size of each region, giving greater weight to variations in more populous areas, which better represents the experiences of the majority in the dataset (Akita and Miyata, 2010). For policy-makers, using population-weighted metrics to understand variations in indicators like income, unemployment, or health outcomes can lead to more effective, targeted interventions. This ensures that policy decisions are aligned with the areas where they can have the greatest impact, based on population distribution (Shankar and Shah, 2003). The formula is:

$$WCV = \frac{1}{\bar{y}} \left[\sum_{i=1}^n p_i (y_i - \bar{y})^2 \right]^{1/2} \quad (1)$$

where y_i represents the value for the i th region, \bar{y} is the average

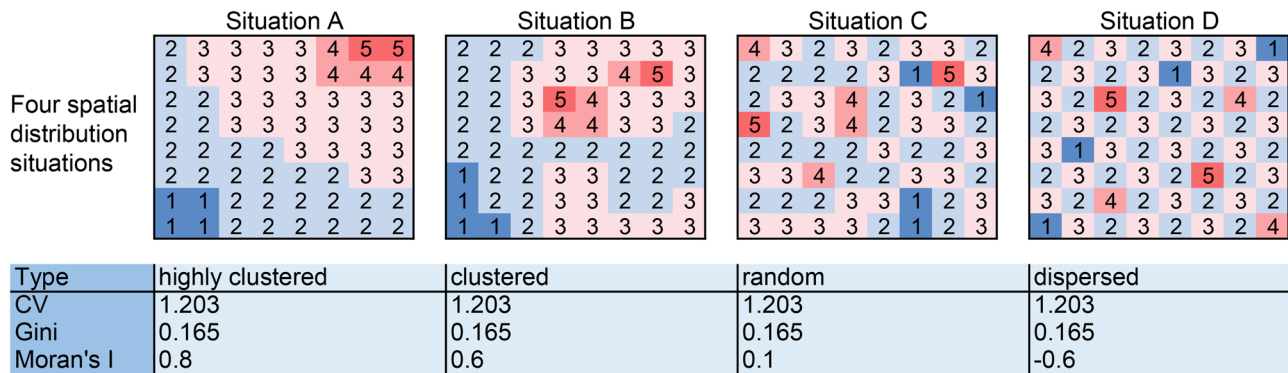


Fig. 3 Different spatial patterns of regional inequality for the same level of spatial inequality.

value across all regions, n denotes the number of regions, and p_i is the proportion of the total national population represented by the i th region. A larger WCV value indicates a higher degree of inequality between regions.

Gini coefficient. The Gini coefficient is another widely utilized indicator for assessing regional inequalities. We employ the Gini coefficient to corroborate the findings derived from the WCV calculations. A higher Gini coefficient signifies more pronounced disparities in regional development. The formula is as follows:

$$Gini = \frac{\sum_{i=1}^n \sum_{j=1}^n |y_i - y_j|}{2n^2 \bar{y}} \quad (2)$$

where y_i and y_j represent values for regions i and j , respectively, n is the number of regions, and \bar{y} is the average indicator value. The Gini coefficient ranges from 0 (complete equality) to 1 (extreme inequality), with values closer to 0 indicating greater equality.

Moran's I. The CV and Gini coefficient, along with other statistical methods, do not fully capture spatial pattern trends. As indicated in Fig. 3, spatial clustering significantly influences regional inequality, and spatial patterns can differ markedly even with similar levels of σ -convergence (Eva et al., 2022). Consequently, we utilized the global Moran's I, the predominant method for detecting spatial autocorrelation (Anselin, 2001; Majumder et al., 2023), to analyze the clustering and dispersion of spatial distributions as follows:

$$Moran's\ I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (3)$$

where n is the number of spatial units; w_{ij} is spatial weights matrix, which represents the adjacency between city i and j ; x_i and x_j represent the observations in city i and j ; \bar{x} is the average of the variable. Moran's $I > 0$ indicates positive spatial autocorrelation among cities (i.e., the presence of geographical clustering), Moran's $I < 0$ indicates negative correlation (i.e., geographical dispersion), and values close to 0 suggesting a random pattern.

Testing the relationship between spatial inequality and economic growth. According to Williamson's hypothesis, an inverted "U"-shaped relationship exists between spatial inequality and economic growth. This study investigates whether such a relationship also persists across economic, social, environmental, infrastructure, and innovation dimensions within China. We employ per capita GDP as a proxy for economic growth and rigorously test the association using three regression equations (Fang et al., 2021). To address issues of outliers and heteroscedasticity, and to enhance model accuracy, we logarithmize the

variables in each equation.

$$\ln Y_t = \beta_0 + \beta_1 \ln x_t + \varepsilon_t \quad (4)$$

$$\ln Y_t = \beta_0 + \beta_1 \ln x_t + \beta_2 (\ln x_t)^2 + \varepsilon_t \quad (5)$$

$$\ln Y_t = \beta_0 + \beta_1 \ln x_t + \beta_2 (\ln x_t)^2 + \beta_3 (\ln x_t)^3 + \varepsilon_t \quad (6)$$

where Y_t represents the inequality index for a given indicator in year t , employing WCV, Gini coefficients, and Moran's I as measures. x_t denotes the per capita GDP in year t , and ε is the random error term. β_1 , β_2 , and β_3 are the estimated coefficients for $\ln x_t$, $(\ln x_t)^2$, and $(\ln x_t)^3$, respectively. The values of the estimated coefficients lead to various curve formations, encompassing seven theoretical configurations: horizontal, monotonically decreasing, monotonically increasing, U-shaped, inverted U-shaped, inverted N-shaped, and N-shaped curves. By calculating the first and second derivatives of the variable Y , we can identify the inflection points for the different curves.

Results

Spatiotemporal evolution of multidimensional spatial inequality in China. A cross-sectional analysis of spatial inequalities across various dimensions reveals that inequality in innovation is currently the most pronounced in China (Fig. 4). Notably, the WCV for per capita granted patents and R&D expenditure consistently exceed 1 across most years, though they have demonstrated a marked decline over the past decade. For the past half-century, most of China's innovation resources, including universities and tech enterprises, have been concentrated in the urban clusters of the eastern region. Despite efforts over the past decade to shift industries to the central and western regions, innovation tends to have strong path dependence, suggesting that inequality in the innovation dimension is likely to persist for an extended period. In contrast, spatial inequality in social metrics is relatively lower, with an average WCV of 0.33, and has shown a declining trend. This reduction is closely linked to China's regional development strategies, such as the Western Development Strategy, implemented over the past 30 years, which have significantly advanced the development of social infrastructure and industries in less developed regions.

Longitudinal analysis since 1990 indicates metrics such as per capita GDP, resident's income, road density, and granted patents follow an inverted U-shaped trend, with recent years showing a narrowing of disparities. The evolutionary trend in the economic dimension has also been confirmed by other literature (He et al., 2017). Conversely, the WCVs for unemployment rates and per capita carbon emissions exhibit a U-shaped trend, with a notable increase in carbon emissions over the last decade suggesting widening regional disparities. To ensure robustness, Gini coefficients for these indicators were also calculated (see Supplementary

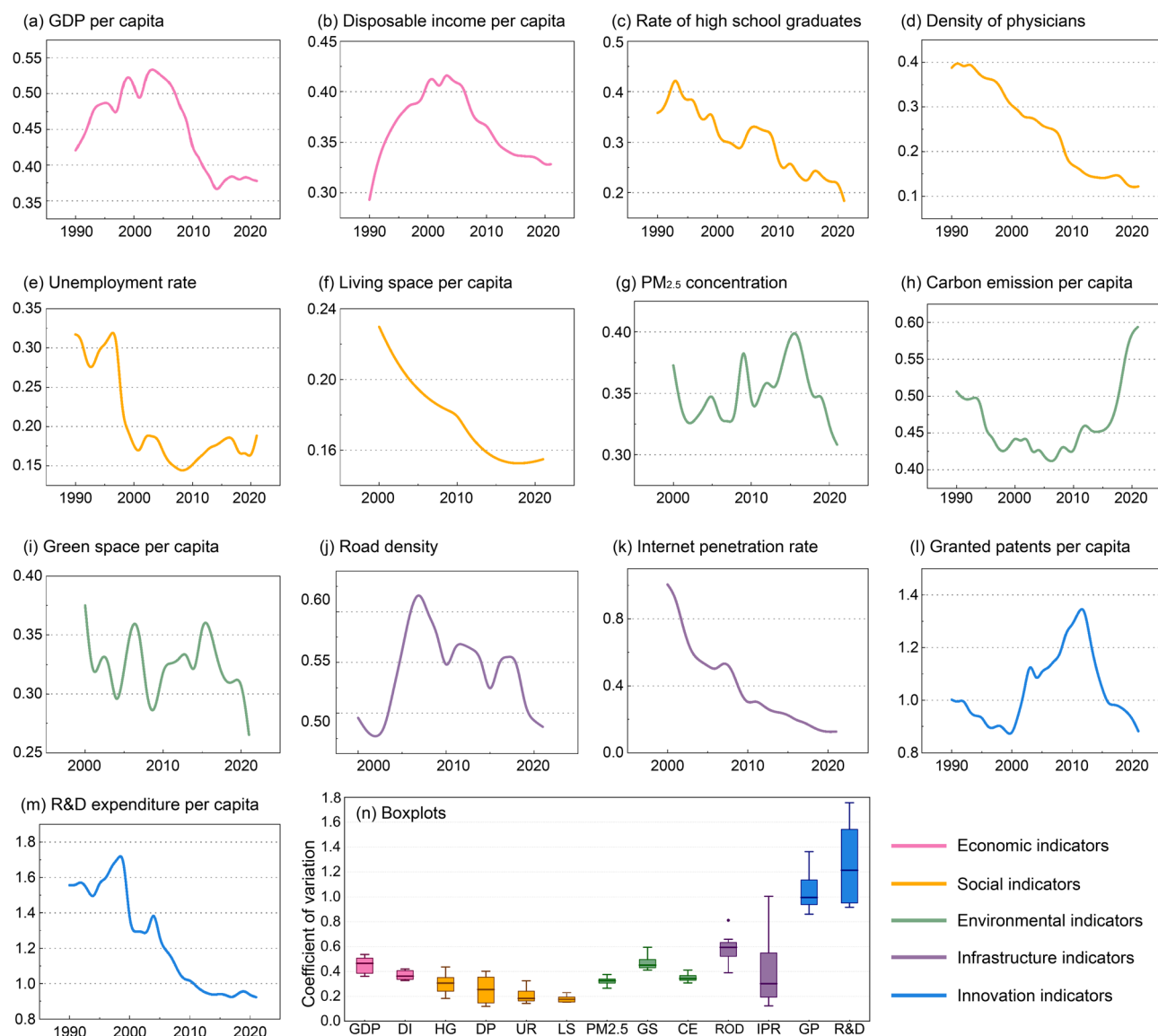


Fig. 4 Temporal evolution of population-weighted coefficients of variation for different indicators. **a** GDP per capita; **b** disposable income per capita; **c** rate of high school graduates; **d** density of physicians; **e** unemployment rate; **f** living space per capita; **g** $PM_{2.5}$ concentration; **h** carbon emission per capita; **i** urban green space per capita; **j** road density; **k** internet penetration rate; **l** granted patents per capita; **m** R&D expenditure per capita; **n** boxplots of WCV.

Fig. S1), confirming consistent temporal trends between the two indices.

Figure 5 presents the global Moran's I results based on contiguity spatial weights, reflecting the extent of spatial clustering within each dimension. From a spatial equity perspective, strong clustering of both high and low values (a spatial Matthew effect) is undesirable as it impedes balanced development. Higher Moran's I values indicate less favorable conditions for spatial equality. Notably, $PM_{2.5}$ and carbon emissions exhibit the highest levels of spatial clustering, with Moran's I values exceeding 0.15, indicating that environmental pollution is concentrated in specific regions of China. Trends in unemployment rates and urban green spaces have shifted from significant to non-significant clustering, while innovation has moved from non-significant to significant clustering. Trends in education consistently show a decline in clustering. GDPpc, income, housing, and per capita physician numbers initially rose then declined, with their spatial clustering weakening in the past decade. This trend suggests that sectors vital to public welfare, like housing, healthcare, and education, are moving towards more balanced spatial development. However, the marked

increases in road density and internet penetration rate highlight a significant spatial Matthew effect in infrastructure, potentially exacerbating regional developmental inequalities, which necessitates increased attention from governmental agencies. To be cautious, we also used the Inverse Distance Weight method to calculate Moran's I for each indicator. The detailed results are shown in Supplementary Fig. S2. We found that the results are generally robust, with no significant changes in the temporal evolution trends for the vast majority of indicators. The only difference is with road density, where the results from the second weighting method indicate that there is no significant change in the spatial clustering of road density.

Figure 6 depicts the annual average change rates of various indicators, capturing the spatial differences in development rates across economic, social, and environmental dimensions among Chinese provinces. Initial and final values for each indicator are detailed in Supplementary Fig. S3. Box plots indicate that growth rates in the innovation and infrastructure dimensions are comparatively faster, whereas those in the social and environmental dimensions lag. Over the past 30 years, China's coastal provinces

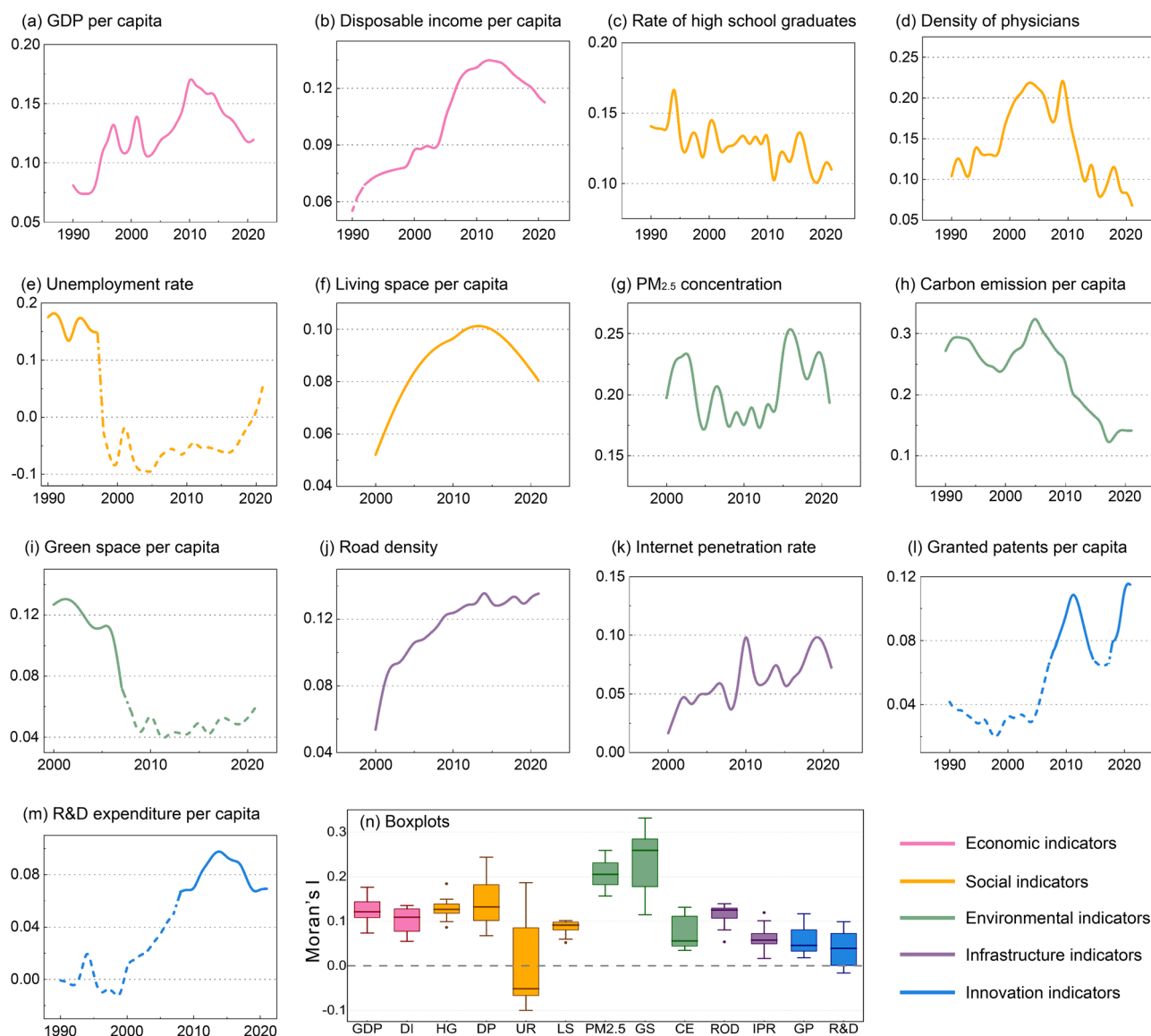


Fig. 5 Temporal evolution of Moran's I for different indicators. **a** GDP per capita; **b** disposable income per capita; **c** rate of high school graduates; **d** density of physicians; **e** unemployment rate; **f** living space per capita; **g** PM_{2.5} concentration; **h** carbon emission per capita; **i** urban green space per capita; **j** road density; **k** internet penetration rate; **l** granted patents per capita; **m** R&D expenditure per capita; **n** boxplots of Moran's I. Solid lines indicate that Moran's I is significant, with a $P < 0.05$; dashed lines indicate nonsignificance, with a $P > 0.05$.

have remained economically advanced, exhibiting rapid growth in per capita GDP, patents, and R&D investment. This trend significantly intensifies the disparities in economic development and innovation between China's eastern and western regions, further exacerbating the already substantial development gap between the two.

Encouragingly, in dimensions such as housing, healthcare, roads, and digitalization, the western and central regions of China generally exhibit higher growth rates than the eastern regions, contributing to a reduction in regional inequalities. In contrast, the Northeast shows growth rates below the national average across economic development, education, roads, and innovation, coupled with a rapidly increasing unemployment rate, suggesting limited effectiveness of recent governmental revitalization efforts in this region. Notably, Xizang demonstrates higher growth rates in economic and social indicators, a development closely tied to substantial fiscal transfers and targeted support from more developed eastern provinces. Similarly, Guizhou, despite being an economically lagging province in western China, ranks high in

growth rates for most indicators, especially income, infrastructure, and innovation. This progress is largely attributed to the province's strategic focus on developing its big data and tourism industries over the past decade.

Relationship between spatial inequality and economic growth

Testing the relationship between WCV for different development indicators and economic growth. Since 1990, China has experienced rapid industrialization and urbanization, with significant economic transformations. In 1990, China's per capita GDP was a mere RMB 1700 (US\$235), classifying it as a low-income country. By 2020, this figure had escalated to RMB 72,447 (US\$10,092), elevating China to middle-income status. By 2023, the per capita GDP further increased to RMB 89,400 (US\$12,358), approaching the high-income country threshold. This section explores how spatial inequalities in economic, social, environmental, infrastructural, and innovation dimensions have evolved in conjunction with China's swift economic progression.

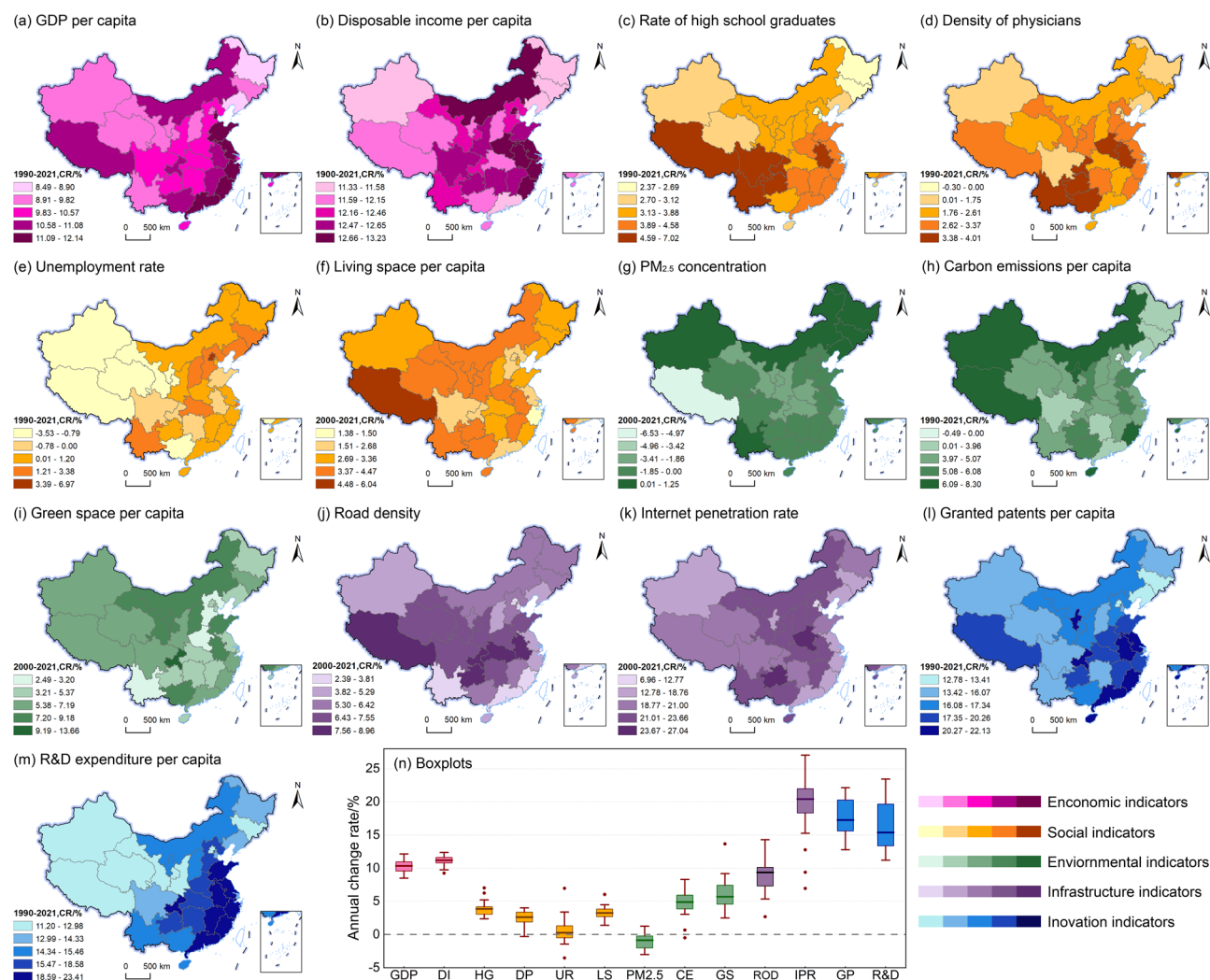


Fig. 6 Annual average change rates for indicators across Chinese provinces. **a** GDP per capita; **b** disposable income per capita; **c** rate of high school graduates; **d** density of physicians; **e** unemployment rate; **f** living space per capita; **g** PM_{2.5} concentration; **h** carbon emission per capita; **i** urban green space per capita; **j** road density; **k** internet penetration rate; **l** granted patents per capita; **m** R&D expenditure per capita; **n** boxplots of annual average change rates. CR change rate.

Using Eqs. 4–6, we evaluated the relationship between per capita GDP and 13 indicators. The optimal model for each indicator was determined based on the model's goodness-of-fit, with results detailed in Table 2 and Fig. 7. Several indicators, including per capita GDP, income, education, healthcare, roads, and internet penetration, demonstrated an inverted U-shaped relationship, with turning points typically below RMB 28,000. Conversely, the fitting curve for the unemployment rate is U-shaped, showing that spatial inequality in unemployment decreases and then increases as economic development progresses. This identifies the temporal turning points for spatial inequality in China's per capita GDP and per capita income around 2004, corroborating previous studies (He et al., 2017; Zhang and Bao, 2015). The observed declining trend in digital inequality over the past decade also aligns with prior research (Liu et al., 2024).

The fitting curve for per capita living space exhibits a consistent decrease, whereas the curve for per capita R&D expenditure follows an inverted U-shape, with turning points below the lowest recorded value of China's per capita GDP since 1990. This indicates that the turning points for these two indicators may have been reached before 1990, and future

economic growth is likely to persistently reduce spatial inequalities in housing and R&D expenditure.

The fitted curve for per capita carbon emissions follows an “N” shape, with turning points at 0.18 and 1.85×10^4 yuan per capita GDP levels, indicating that carbon emission inequality may continue to rise, while Wang et al. (2019) highlighted a decline in the inequality of China's carbon emission intensity. The fitted curves for PM_{2.5}, per capita green space, and granted patents per capita exhibit an inverted “N” shape. Given that China has already surpassed the second turning point for these indicators, spatial inequality in these areas is likely to decrease further. Liu et al. (2023) reported a significant reduction in PM_{2.5} exposure and its spatial disparity post-2010, consistent with our findings.

To assess the robustness of our findings, we conducted a regression analysis using the Gini coefficient as a substitute for WCV (Supplementary Table 1). The results indicate that, although the dependent variable is changed, the shape of the fitted curves for various indicators remains largely unchanged, with only slight variations in the inflection points. This suggests that WCV and the Gini coefficient yield consistent measurements of provincial-level inequality in China.

Table 2 Regression results of economic growth and WCV of 13 indicators.													
	GDP	DI	HG	DP	UR	LS	PM2.5	CE	GS	ROD	IPR	GP	R&D
lnx	-0.03***	0.02***	-0.14***	-0.31***	-0.22***	-0.17***	-0.24	-0.10***	-0.20*	0.30***	-0.47***	0.25***	-0.16***
lnx2	-0.07***	-0.07***	-0.04***	-0.07***	0.08***		0.39*	0.05***	0.42**	-0.14***	-0.19***	0.01	-0.03***
lnx3							-0.14*	0.03***	-0.16**			-0.08***	
_cons	-0.68***	-0.91***	-1.10***	-1.22***	-1.65***	-1.55***	-1.13***	-0.86***	-1.10***	-0.69***	-0.28***	0.02	0.31***
N	32	32	32	32	32	22	22	32	22	22	22	32	32
adj.R ²	0.86	0.91	0.85	0.97	0.70	0.97	0.09	0.85	0.24	0.67	0.96	0.74	0.88
F	93.26	160.89	86.14	614.20	36.66	708.20	1.67	58.33	3.23	21.97	243.44	31.03	115.60
P	0.00	0.00	0.00	0.00	0.00	0.00	0.21	0.00	0.05	0.00	0.00	0.00	0.00
Curve shape	"inverted U"	"inverted U"	"inverted U"	"inverted U"	"U"	negative linear	"inverted N"	"N"	"inverted N"	"inverted U"	"inverted U"	"inverted N"	nonlinear descent
Turning points	0.84	1.19	0.17	0.12	4.05	none	(1.49, 4.10)	(0.18, 1.85)	(1.33, 4.35)	2.71	0.30	(0.38, 2.90)	meaningless
P (White)	0.29	0.02	0.24	0.10	0.12	0.42	0.20	0.05	0.31	0.94	0.09	0.59	0.09
P (SW)	0.20	0.44	0.21	0.23	0.01	0.15	0.77	0.78	0.42	0.45	0.36	0.37	0.001
***, ** and * represent significant at 1%, 5% and 10% levels, respectively. The unit of the turning points is 10,000 yuan. P (White) ≥ 0.01 implies that the model does not exhibit heteroscedasticity. P (SW) ≥ 0.01 indicates that the residuals can be considered normally distributed.													

Testing the relationship between Moran's I for different development indicators and economic growth. Due to the non-significance of Moran's I for indicators such as unemployment rate, green space, R&D, and patents in most years, this section focuses exclusively on analyzing the spatial clustering of the remaining nine significant indicators and their relationship with economic growth. Using Eqs. 4–6, the relationship between each indicator and per capita GDP is examined. The optimal fitting model for each indicator, determined based on goodness-of-fit, is presented in Table 3 and Fig. 8.

Per capita GDP, income, housing, carbon emissions, and roads all exhibit an inverted U-shaped evolution trend. Although physician density shows an inverted N-shape, its first inflection point is minimal, allowing it to be approximated as an inverted U-shape. This suggests that in these five areas, China initially experiences spatial agglomeration with economic development, followed by spatially balanced development after reaching a certain turning point. Only PM_{2.5} follows a U-shaped evolution trend, with a turning point at 24,100 RMB (around 2009). Despite significant improvements in air pollution control after 2013, the spatial agglomeration of PM_{2.5} has intensified. Unlike the declining WCV in internet penetration, its spatial agglomeration has shown a significant upward trend.

Discussions

Policy implications. Although spatial inequality in China's infrastructure and innovation is overall decreasing, the distribution is becoming more concentrated. This trend aligns with the continuous clustering of digital industries and technological resources in urban agglomerations. Research indicates that digital development aids in narrowing regional disparities (Liu et al., 2024). Therefore, the Chinese government should prioritize enhancing digital infrastructure and investing in technological education in underdeveloped regions. In the current era of digitalization and intelligence, it is essential to prevent the widening of the digital divide, which could foster new inequalities.

Data from China indicates that sustained economic growth reduces spatial inequality across most dimensions, except for unemployment and carbon emissions. For metrics exhibiting an inverted U-shaped pattern, China's development stage has already surpassed the turning point, suggesting that future economic growth will likely further diminish inequality. Thus, mitigating spatial inequality requires not only policy interventions—such as fiscal reallocation, ecological compensation, and strategic project placement—but also continuous, healthy macro-economic development. In the post-pandemic era, however, China faces multiple pressures: insufficient domestic demand, challenges in economic restructuring, and Sino-US trade frictions. Amid slowing economic growth, the government must strike a better balance between achieving spatial equality and maintaining rapid development.

The decline of the Northeast region in China warrants special attention, as it has lagged behind the national average in various aspects of economic development, education, road infrastructure, and innovation, accompanied by a rapidly increasing unemployment rate. To address this issue, the government should provide strong support for industrial transformation and upgrading, diverting funds and policies towards technological innovation, information technology, and green industries, and promoting the digitalization and intelligent transformation of traditional industries. Furthermore, it is essential to focus on talent introduction and cultivation, strengthening education and vocational training. Similarly, Xinjiang's 30-year socioeconomic development has also been slower than the national average. To overcome this, it is

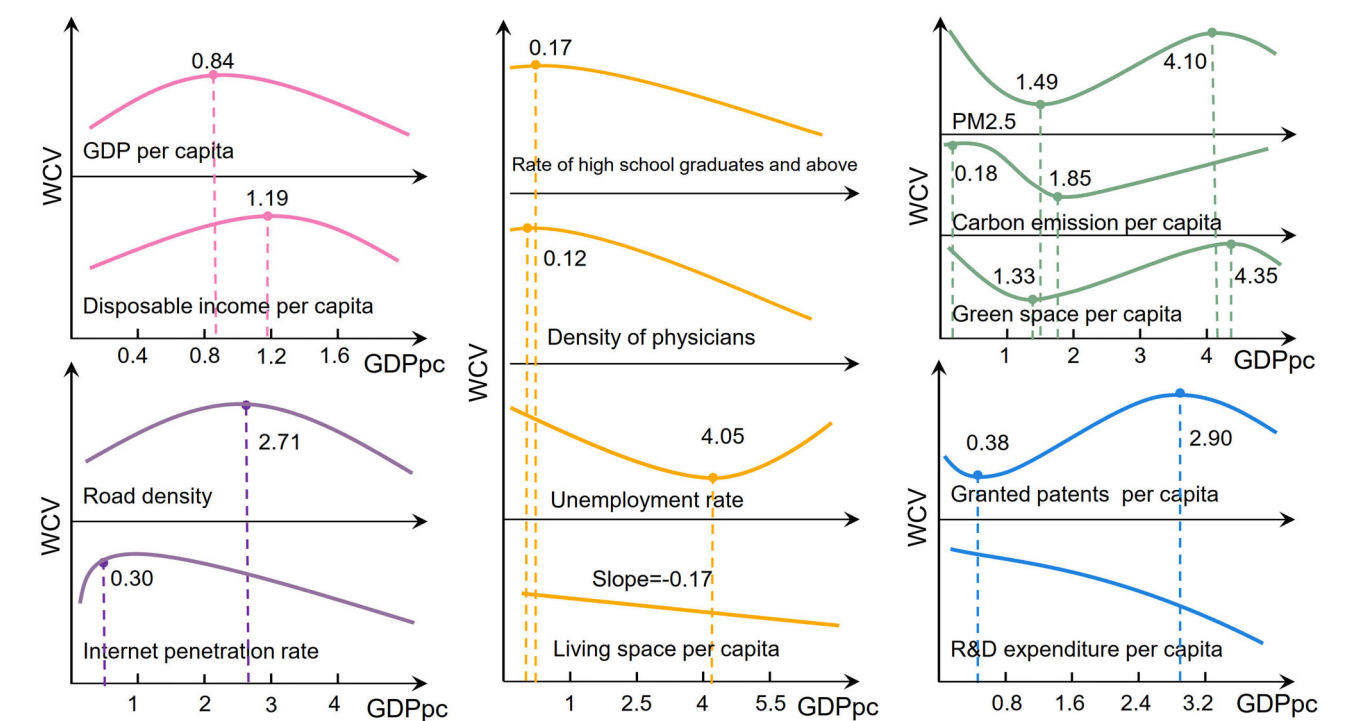


Fig. 7 Coupling curves of economic growth and the WCV of development indicators. The unit for GDPpc is 10,000 yuan.

Table 3 Regression results of economic growth and Moran's I of 9 indicators.									
	GDP	DI	HG	DP	LS	PM2.5	CE	ROD	IPR
lnx	0.20***	0.51***	-0.06***	0.26***	0.66***	-0.29**	-0.13***	0.53***	0.42***
lnx2	-0.07***	-0.19***		-0.18***	-0.26***	0.16**	-0.11***	-0.19*	
lnx3				-0.09***					
_cons	-2.10***	-2.39***	-2.04***	-1.71***	-2.72***	-1.56***	-1.25***	-1.68***	-3.32***
N	32	32	32	32	22	22	32	22	22
adj.R ²	0.69	0.88	0.24	0.69	0.96	0.15	0.77	0.37	0.47
F	35.17	75.63	10.88	23.80	256.10	2.86	52.57	7.08	19.62
P	0.00	0.00	0.01	0.00	0.00	0.08	0.00	0.01	0.00
Curve shape	"inverted U"	"inverted U"	negative linear	"inverted N"	"inverted U"	"U"	"inverted U"	"inverted U"	positive linear
Turning points	3.98	3.90		0.16, 1.67	3.55	2.41	0.58	4.02	
P(White)	0.81	0.39	0.84	0.21	0.13	0.87	0.58	0.33	0.41
P(SW)	0.09	0.08	0.83	0.83	0.23	0.07	0.53	0.001	0.30

***, ** and * represent significant at 1%, 5% and 10% levels, respectively. The unit of the turning points is 10,000 yuan. P (White) ≥ 0.01 implies that the model does not exhibit heteroscedasticity. P (SW) ≥ 0.01 indicates that the residuals can be considered normally distributed.

recommended that Xinjiang leverage its geographical and cultural proximity to Central Asian countries to promote economic cooperation with neighboring nations, develop cross-border e-commerce and logistics, and tap into its geographical and climate advantages to vigorously develop clean energy such as wind power and solar power.

Some scholars argue that economic and environmental indicators in the SDG goals often entail trade-offs (Pradhan et al., 2017). However, our research reveals a nonlinear relationship between these indicators, varying across different development stages. For instance, PM_{2.5} concentration, per capita green space, and per capita GDP exhibit inverted N-shaped relationships. Wu et al. (2022) found similar results through network analysis. This suggests that policies should be tailored to the specific stage of development, promoting dynamic and differentiated strategies for human-nature harmonious development. Particularly during stages that involve trade-offs, stronger policy regulation is essential.

Research limitations. Despite our study’s extension of Williamson’s hypothesis and the clear findings presented, certain limitations remain. Although our time series data is the longest available compared to previous studies, it remains insufficient for fully validating macro-regional development patterns, especially for the five indicators with data only starting from 2000, which may impact the reliability of the results. However, based on China’s 1990s development trajectory, we can qualitatively estimate these trends. The internet only became widespread after 2000, making it appropriate to start our analysis from that year. Macroeconomic data show that real estate development and road infrastructure construction steadily increased between 1990 and 2010 (Banerjee et al., 2020). PM_{2.5} levels, closely linked to primary energy consumption, also followed a steady upward trend from 1990 to 2013 (Wang et al., 2020). Additionally, legislation for urban greening introduced in 1992 led to systematic development of urban green spaces. Thus, it is reasonable to infer that the

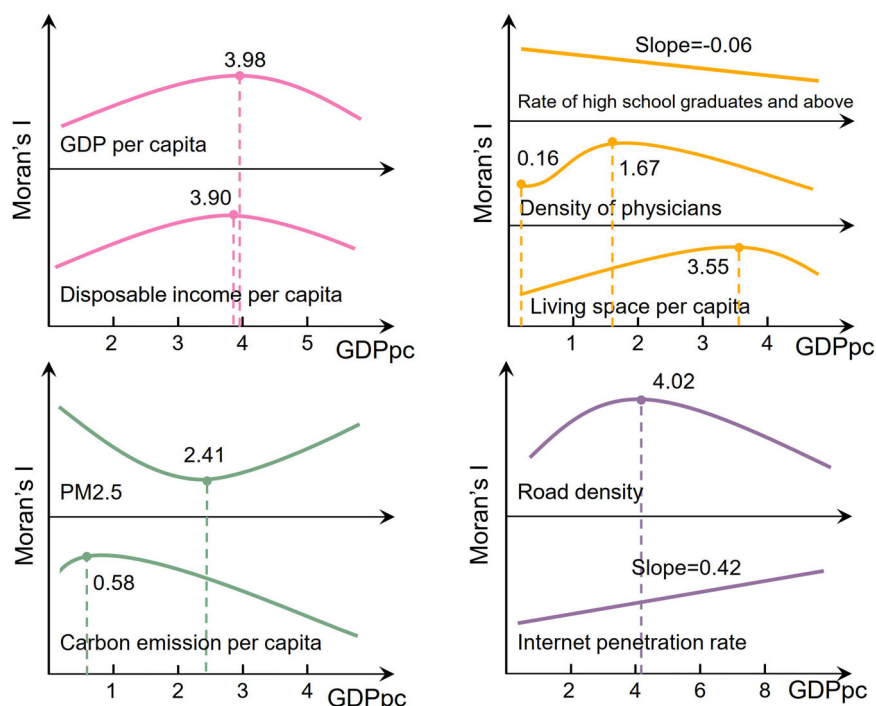


Fig. 8 Coupling curves of economic growth and the Moran's I of development indicators. The unit for GDPpc is 10,000 yuan.

1990s trends for these indicators largely align with those observed in the early 2000s.

Our findings indicate a growing spatial concentration of innovation factors in China, a trend that presents both opportunities and challenges. While numerous studies suggest that such clustering enhances economic output and efficiency (Delgado et al., 2014), it may impede the capacity of underdeveloped regions to achieve leapfrog development. This study highlights the existence of this concentration but refrains from an in-depth exploration of its potential benefits and drawbacks. Our conclusions are derived from statistical and regression analyses of indicator data, and the mechanisms underlying these trends require further investigation. Additionally, this study uses data exclusively from China. The relationship between spatial inequalities in social, environmental, infrastructural, and innovation dimensions and economic growth needs to be validated with data from other countries and regions.

Conclusions

China currently exhibits the highest spatial inequality in innovation and the lowest in the social dimension. Since 1990, spatial inequalities in most indicators have shown a downward trend. However, in the past decade, inequalities in unemployment rates and carbon emissions have started to rise. Environmental indicators such as PM_{2.5} concentrations and carbon emissions demonstrate the highest degree of spatial clustering. Sectors crucial to public welfare—namely housing, healthcare, and education—are moving towards more equitable spatial distribution. Conversely, the increasing spatial clustering of road density and internet penetration underscores the spatial Matthew effect in infrastructure development in China. Over the past 30 years, the gap between China's eastern coastal regions and the central and western regions has widened in terms of economic development and innovation. Additionally, the growth rates of most indicators in the northeastern region have fallen below the national average, suggesting the limited efficacy of the Northeast Revitalization Strategy.

The case of China demonstrates that Williamson's inverted U-shaped hypothesis extends beyond the economic domain to encompass education, healthcare, infrastructure, and digitalization. However, this pattern is not observed in environmental metrics, housing, or innovation. Notably, our calculations using Moran's I reveal that the spatial clustering of per capita GDP, income, housing, carbon emissions, roads, and healthcare also exhibits an inverted U-shaped evolutionary trend in relation to economic growth. Additionally, we revealed the nonlinear relationship between economic and environmental indicators, providing new insights for the dynamic adjustment of policies. We look forward to future case studies from more countries and regions to engage in dialog with our findings.

Data availability

All data used in this study were obtained from official databases, and the specific sources are described in detail in the "Data and Methods" and "Notes" sections. These data can also be found in the Supplementary Information. If necessary, the datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

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Notes

- 1 China's 2035 Objectives is the highest-level strategic plan formulated by the central government of China in 2021 to guide the country's development for the next 15 years. The Chinese version is available at: https://www.gov.cn/xinwen/2021-03/13/content_5592681.htm.
- 2 China Internet Development Report (in Chinese) is available at: <https://www.isc.org.cn/category/7356.html>. Please describe panels a-n in fig 5 legend.
- 3 The MEIC website: http://meicmodel.org.cn/?page_id=1772&lang=en. Please describe panels a-n in fig 5 legend.

4 PM_{2.5} concentrations from Washington University in St. Louis: <https://sites.wustl.edu/acag/datasets/surface-pm2-5/>.

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Haimeng Liu: conceptualization, data curation, resources, visualization, writing—original draft & review, funding acquisition. Liwei Wang: data analysis, formal analysis, supervision, writing – review & editing. Jinzhou Wang, Hangtian Ming, and Xuankuang Wu: methodology, software, visualization, writing—original draft. Gang Xu: supervision, writing—review & editing. Shengwu Zhang: project administration, validation, writing—review & editing, funding acquisition.

Competing interests

The author declares no competing interests.

Ethical approval

There are no experiments carried out using the human population for this research.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

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