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RETRACTED: Spatial–Temporal Characteristics and Determinants of Digital Divide in China: A Multivariate Spatial Analysis

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Abstract: The digital divide has loomed as a sustainable development issue for over two decades and there has been much research in terms of efforts to measure the digital divide from different dimensions and scales. Drawing on spatial agglomeration analysis and multiple linear regression, this paper aims to reveal the spatiotemporal pattern of the prefectural digital divide in China and its determinants. The results show that there is a significant prefectural digital divide in China that is characterized by a decline of ICT development index (IDI) values from the east to the west as well as from core cities to more peripheral ones. Cities with high IDI values are mainly concentrated in large metropolitan areas in eastern China, whereas cities with low values tend to concentrate in poverty stricken regions in central and western China. However, the digital divide has been characterized by a reduction from 2001 to 2015. The results also show that both economic and educational factors have significant influences on the prefectural digital divide in China. During the early stages, the percentage of university students, urban residential income, and the urbanization rate were key factors. However, after 2010, the adult literacy rate and rural residential income determined the digital divide.

Keywords: digital divide; ICT development index; spatial–temporal characteristics; spatial correlations; impact factor

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1. Introduction

It is now widely accepted that the world is moving rapidly into the information age, and that information and communication technologies (ICTs) are major components of this historic transformation [1]. Furthermore, it is arguable that no aspect of technological progress over recent decades can match the profound and extensive influence of ICTs [2]. However, there is huge inequality in ICT access and use all over the world, which has been termed the "digital divide" [3–5]. A plethora of studies have been conducted to measure the digital divide and identify its determinants [2,6–11]. OECD (Organization for Economic Co-operation and Development) defines digital divide as "the gap between individuals, households, businesses and geographic areas at different socioeconomic levels with regard both to their opportunities to access ICTs and to their use of the Internet for a wide variety of activities" [12]. Indeed, both the societal diffusion and spatial distribution of ICTs are hugely uneven at all scales. Furthermore, several scholars have labelled the first- and second-order digital divide regarding the huge inequality in ICT access and use [3–5,7,8,13–15]. However, to date, there has been little research on the second-order digital divide at the under-country scale, such as regional, prefectural, or city level.

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In this study, we focus on the first- and second-order digital divide and try to investigate the prefectural digital divide in China. China is an important area of research, as it has developed to become one of the fastest growing global ICT markets since connecting to the Internet in 1994. In 2018, China is among the top two nations worldwide in terms of total internet users and mobile cellular telephone subscriptions [16,17], with approximately 56.7 million internet hosts (second in number only to the United States) and almost 829 million internet users (largest in the world). As China is also a large and increasingly diverse nation socially, politically, economically, and demographically, significant spatial differences in ICT access and use have developed between provinces and prefectural cities. China is the world's largest populous country with a population of 1.3 billion and one of the largest countries with an area of 9.6 million square kilometers. There are 31 provinces and 334 prefectural cities in mainland China, to the exclusion of Taiwan, Hong Kong, and Macao. A prefectural-level city is an administrative division that ranks below a province and above a county in the national administrative structure.

The aims of this paper are to develop a theoretical model of digital divide for prefectural cities in China, to examine the spatial distribution and spatial agglomeration of ICT access and use nationally, and to explore the leading drivers of the prefectural digital divide based on social, political, and economic variables. Based on these results, this study then aims to provide policy, management, planning, and decision-making recommendations for the sustainable development of ICTs in China and developing countries. The main research questions were regarding what the spatiotemporal characteristics of ICT access and use at the prefectural level in China are and which factors determine the prefectural first- and second-order digital divide.

This study has a number of novel attributes when compared to existing literature. Firstly, a theoretical model encompassing socioeconomic correlates of the digital divide is constructed at the prefectural level. This approach is important because existing research on the digital divide has mainly been carried out at the level of macro-regions and provinces. Theoretical models for the digital divide at the provincial level in China as well as in other nations have already been presented [18–22], including county- and city-level theoretical models for the United States [23,24]. To date, however, no systematic nationwide analysis of the digital divide has been undertaken at the prefectural level in China, and so knowledge of the drivers of this phenomenon remains limited. Secondly, it answers calls for multiple-level studies and thereby substantially extends comparative empirical examinations of the digital divide [4,7,25]. This paper analyses the spatiotemporal characteristics of ICT access and use in China at the prefecture level and explores the evolution and transformation of important determinants of the first- and second-order digital divide between 2000 and 2015. As existing literature on the digital divide is entirely focused on data from single years, no research to date has addressed the evolution of ICT use and its transformation based on multivariate correlates. Thirdly, spatial analysis and mapping methods are applied in this paper that significantly supplement traditional multivariate analyses [10]. We exploit the visualization capability of the software ArcGIS to develop a descriptive understanding of geographic patterns of the digital divide and utilize a spatial autocorrelation model to analyze the agglomeration of ICTs and to identify ICT use in hot and cold spots within cities. We then evaluate the regression residuals generated by this approach using spatial autocorrelation to mitigate the effects of spatially biased regression findings.

2. Theoretical Framework for the Digital Divide

2.1. Measuring the Digital Divide

2.1.1. Theoretical Background

A wide range of studies have sought to measure the digital divide and capture its multidimensionality employing composite indicators or indices [2,7,25–27]. Early research mainly focused on the internet and the diffusion of new technologies (e.g., DSL, cable, or wireless), especially the overall ability of individuals to access the internet, which is now referred to as the first-order digital divide [28–31]. The approach to the first-order digital divide was a simplistic study of the uneven distribution of Internet access [4,31–35], observed by the number of computers, mobile phones, internet service providers (ISPs), and internet users [7,28,36]. Some studies have also focused on the cost of internet access and internet skills [14,37]. For example, Dewan and Riggins [7] referred the first-order digital divide as the inequality of access to IT, such as access to computers in homes and schools. Friedman [38] described ICT access inequality as the narrow sense of the digital divide. Van Dijk [4] measured ICT usage access by computer use, internet use, broadband use, usage time and cost of internet usage (Table 1).

Since 2003, studies dealing with the digital divide have been extended to examine ICT use, which is now known as the second-order digital divide [10,13,14,39,40]. For example, the digital inequality index proposed by the International Telecommunication Union (ITU) [41] considers such factors as internet users per 100 inhabitants, computer per 100 inhabitants, mobile cellular subscribers per 100 inhabitants, internet bandwidth per capita, and broadband internet subscribers per 100 inhabitants. Lenhart et al. [42] measured the digital divide in America in terms of the communication channels and capacity, number of computers, fixed telephone line penetration, mobile cellular penetration, internet use frequency, time online, and internet access price. In later work, Kim [43] proposed that ICT utilization can be assessed using a composite measure, an approach which has attracted increasing attention from researchers, and a comprehensive study of relevant literature reveals several additional promising aspects that could be considered when appraising the use of these technologies. Nishida et al. [22] and Pick et al. [10] further suggested the inclusion of a netizen factor within analyses, such as the number of Facebook, Twitter, or Instagram users, while Park [44] and Zhu and Chen [21] suggested the inclusion of e-commerce-related factors, such as business-to-business (B2B), business-to-customer (B2C), and e-governance variables (Table 1).

Table 1. Summary of variables for measuring the digital divide.

Category	Variable	Code	Support
Access	Fixed telephone penetration	I_1	[12,26,31,33,45,46]
	Mobile phone penetration	I_2	[12,26,31,32,41,45,47]
	Computer penetration	I_3	[12,26,32,41,48–50]
	Number of internet service providers (ISPs)	I_4	[32,50,51]
	Internet access price	I_5	[6,12,26,31,41,42,48]
	Mobile phone expenditure	I_6	[31,32,42,49]
	Websites per capita	I_7	[17,31,45,47,48,52]
Use	Internet users per capita	I_8	[6,12,26,31,41,42,47,49,50,53–55]
	E-commerce users	I_9	[21,56,57]
	Frequency	I_{10}	[14,42,46,47,50,58]
	Time online	I_{11}	[14,42,47,50,57]
	Broadband subscribers	I_{12}	[6,26,33,58]
	Netizens in social networks	I_{13}	[10,21,22,44]
	Internet bandwidth	I_{14}	[26,33,55]

2.1.2. Indicator Selection

Constructing a composite measure for the digital divide poses several substantial methodological challenges [6] and necessitates a serious re-examination of currently utilized measurement indicators [45]. There is usually a trade-off between the number of indicators and territories that can be included in research, which could affect the accuracy of any measures for a prefectural-scale digital divide [49,52,53]. Given this constraint, the indicators used in measurements should be carefully examined initially [45].

First, based on a literature review, we initially summarized 14 indicators from the existing literature (Table 1). Because the index should be as national as possible, the availability of the data (and their quality) for every prefectural city in China was examined. As ICT data availability in the majority of cities is poor, this was the main restrictive factor in data selection. Three indicators were deleted from our consideration here, namely I_4, I_{10} and I_{11}.

Second, we performed a principal component analysis (PCA) to analyze the underlying nature of these data. This enabled us to explore whether different dimensions are statistically well balanced and reveal how indicators associate and change in relation to one another. The results of this PCA enabled us to identify the relative importance of these 14 indicators and assign a relative value to each indicator.

Third, we used a fuzzy analytic hierarchy process (FAHP) to statistically revise these weights and to provide a definition of the components of each indicator [59]. The first step was to develop a series of judgment matrices, defined as the reciprocal comparisons of indicators, as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{1}$$

where R is the judgment matrix that expresses the importance of each indicator, while r_{mn} is the priorities indicator of m relative to n, and m and n denote the number of indicators. It therefore follows that:

$$r_{mn} = f\ (w_m - w_n) \tag{2}$$

where w_m denotes the weight of the m indicator, while w_n is the weight of the n indicator, as follows:

$$\begin{array}{c|cccc} S_i & I_1 & I_2 & \ldots & I_m \\ \hline I_1 & r_{11} & r_{12} & \ldots & r_{1m} \\ I_2 & r_{21} & r_{22} & \ldots & r_{2m} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ I_n & r_{n1} & r_{n2} & \ldots & r_{nm} \end{array} \tag{3}$$

where S_i denotes the judgment matrix of the importance of the i sub-index, while I_m is the m indicator.

The second step was to derive a series of weights for our indicators from these judgment matrices, and implemented a consistency check in each case, as follows:

$$r_{ij} = 0.5 \pm a\ (w_i - w_j),\ i,j = 1, 2, \ldots, n \tag{4}$$

where w_i is the weight of the i indicator, while w_j is the weight of the j indicator.

On this basis, we finally identified five indicators that comprise the ICT development index (IDI) (Table 2), namely, fixed telephone penetration (I_1), mobile cellular penetration (I_2), PC penetration (I_3), internet users per capita (I_8), and broadband subscribers per capita (I_{12}).

Table 2. Information communication technology (ICT) development index (IDI) and the weights of indicators.

Index	Sub-Index	Weight	Indicator	Weight
IDI	ICT access	48%	Fixed telephone penetration	12%
			Mobile cellular penetration	18%
			PC penetration	18%
	ICT use	52%	Internet users per capita	25%
			Broadband subscribers per capita	27%

2.2. A Conceptual Model of the Digital Divide

We identified a number of theoretical models and frameworks that explore socioeconomic influences on the digital divide based on a comprehensive literature review. For example, King et al. [60] considered the influence of institutional factors on technology utilization, including the supply and demand of these variables alongside institutional regulations, while Agarwal et al. [61] suggested that social factors such as education, income, gender, and ethnicity, as well as geographical proximity, have impacted on the digital divide within metropolitan areas of the United States. Pick and Azari [62] went further to consider government support, legal frameworks, and social openness as intermediate factors influencing socioeconomic level, which in turn influence technology utilization. We therefore included geographical, institutional, social, and economic factors as components in our models.

Studies have consistently determined drivers of the digital divide within a diverse hierarchy, including globally [62,63], nationally [48,64], provincially and at the level of individual states [20,22], as well as at county and city levels [23,24,65], and at the level of individuals [66]. Although a number of theories and modeling approaches have been proposed to explain the multivariate correlates of technology utilization, there has so far been an absence of well-accepted theoretical models at the prefectural level in China, especially for cities within this hierarchy.

On the basis of existing theories and modeling approaches, a specific conceptual model was therefore established to investigate and explain spatiotemporal patterns of ICT use in China. Indeed, as we consider the digital divide to comprise a multi-dimensional set of phenomena, a variety of dependent factors were included in this analysis [62,63,67–72]. A series of independent variables were also culled from the digital divide literature and grouped into categories. The conceptual model is presented in Figure 1.

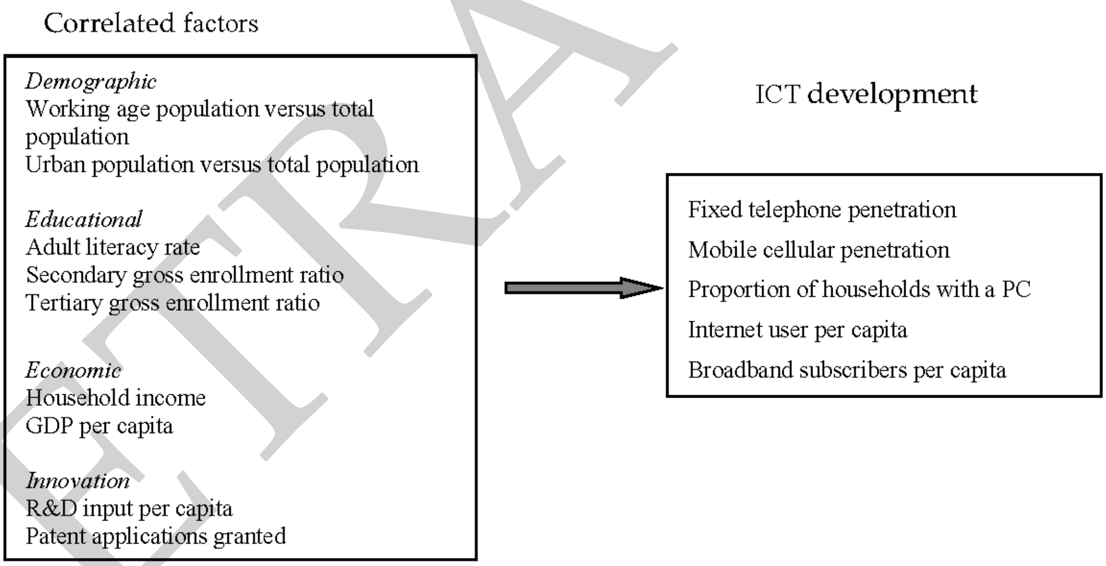


Figure 1. The conceptual model of ICT development.

2.2.1. Demographic Factors

It is well known that demographic factors impact the adoption and use of ICTs [22]. This is especially the case in China where the workforce has become technologically enabled and is one of the largest and most productive in the world; given the development of mobile terminals, electronic commerce and payments in recent years, the use of ICTs in production and consumption within Chinese industries has been a high priority. We therefore hypothesize that the working age population ratio will be correlated with the use of ICTs.

There are also marked global urban–rural differences in technology utilization; in China, the poor infrastructure of rural areas and commonplace surrounding mountainous terrain have reduced ICT use in the bulk of these regions [18,19]. In contrast, ICT use in urban areas has been markedly enhanced in Chinese urban areas; we therefore also hypothesize that the ratio between the urban and total population will be correlated with enhancements in ICT use.

2.2.2. Educational Factors

Our review of the literature reveals that education has broad significance in terms of technology utilization [10,48,72,73]. Across a Chinese national sample of individuals, college education was found to among the most important determinants of personal computer (PC) use in the early 21st century [32,51]. In contrast to this result, however, it is also the case that more and more people with basic literacy have begun to utilize personal ICTs within China, in part because mobile phones and PCs have themselves become much more intelligent [46,74]. An emphasis on education both within households and at the prefectural level fosters ICT skills, which stimulates the readiness of people and organizations within these geographic regions to adopt and use ICTs [22]. We therefore hypothesize that three determinants will be correlated with an increase in ICT use, the adult literacy rate and the secondary- (SER) and tertiary-level (TER) education gross enrollment ratios.

2.2.3. Economic Factors

Economic influences on ICT utilization stem from favorable prefectural economies that include higher income levels that enhance the affordability of ICTs [22] as well as more developed economies that foster the utilization of these technologies [33]. Previous large-scale surveys of Chinese households have suggested that income level is among the most important determinants of internet penetration [46], while income per capita is related to PC ownership [19]. As more and more people have started to use online stores (e.g., taobao.com, jd.com), the existence of a PC in the home is positively correlated with personal income, especially in the case of part-time employees and unemployed people. Individuals and households within China with higher incomes are better able to afford ICT costs, while higher prefectural per capita gross domestic product (GDP) stimulates more investment in these technologies by government and organizations [22]. We therefore hypothesize that household and prefectural income will increase ICT utilization and expenditure.

2.2.4. Innovation Factors

Innovation factors are known as correlates of ICT use in China [74], the United States [65,75], Japan [22], Europe [76], and worldwide [73]. Data show that the most important determinant of this trend globally has been the availability of scientific and technical journal articles [73], while in the United States, research and development (R&D) expenditure catalyzes the use of computers and the Internet, especially broadband [75]. Similarly, R&D activity in Japan has increased technology utilization and expenditure [22], while in China, the government has emphasized national and regional innovation by improving input in this area and encouraging patent applications which can then foster direct use of ICTs and indirect regional economic growth. We therefore hypothesize that R&D input and patent applications are correlated with increases in the use of ICTs.

3. Methods and Data Sources

3.1. Data

One of the main constraints on analyses of the digital divide is data availability [53]. In China, governments and organizations such as the Ministry of Industry and Information Technology and the China Internet Network Information Center (CNNIC) have responsibility in this area. At the same time, more and more comparable ICT data are becoming available at national and provincial levels, which can help the authorities to track the ICT development. Nevertheless, it remains difficult to collect data on ICT access and use at prefectural level.

In light of these limitations, a variety of data were collected from different sources for use in this study (Table 3). ICT data for the prefectural cities in mainland China (not including Hong Kong, Macao, and Taiwan) were extracted from the China City Statistical Yearbook (CCSY), the 31 Provincial Statistical Yearbooks (PRSY), and from the Statistical Report on Internet Development in China (SRID). Demographic and educational data at the prefectural level were obtained from the Chinese sixth national population investigation, while economic data were culled from the China City Statistical Yearbook, and innovation data were extracted from the 31 Provincial Statistical Yearbooks on Science and Technology (PSYST). E-commerce economy and online shopping benefits data were obtained from the Alibaba Group, which are collected by the Ali Research Institute and are not publicly available. We collected internet price data and broadband subscriber data from the homepages of internet broadband service companies, including China Mobile, China Unicom, and China Telecom.

Table 3. Dependent and independent variables used in this study.

Category	Variable	Code	Source *	Year(s)
Dependent Variables				
ICT access	Fixed telephone penetration	I_1	CCSY	2001–2015
ICT access	Mobile cellular penetration	I_2	CCSY	2001–2015
ICT access	Proportion of households with a PC	I_3	PRSY	2001–2015
ICT use	Internet users per capita	I_8	SRID	2001–2015
ICT use	Broadband subscribers per capita	I_{12}	COMP	2001–2015
Independent Variables				
Demographic	Proportion of working age population	WAP	CNPIR	2000, 2005, 2010
Demographic	Proportion of urban population	URB	CNPIR	2000, 2005, 2010
Educational	Adult literacy rate	ALR	PRSY	2001–2015
Educational	Secondary gross enrollment ratio	SER	PRSY	2001–2015
Educational	Tertiary gross enrollment ratio	TER	PRSY	2001–2015
Economic	Residential income per capita	PIN	CCSY	2001–2015
Economic	GDP per capita	GDP	CCSY	2001–2015
Innovation	R&D input per capita	RDI	PSYST	2001–2015
Innovation	Patent applications granted	PAG	PSYST	2001–2015

* Abbreviations: CCSY, China City Statistical Yearbook; PRSY, Provincial Statistical Yearbooks; SRID, Statistical Report on Internet Development; COMP, the three internet broadband service companies in China, including China Mobile, China Unicom, and China Telecom; CNPIR, Chinese National Population Investigation Report; PSYST, Provincial Statistical Yearbooks on science and technology.

3.2. Methods

3.2.1. Spatial Agglomeration Analysis

We applied a spatial autocorrelation model to analyze agglomerations of ICT use. To do this, we applied the First Law of Geography, in which any object is related to others given the special consideration of distance; thus, the more closely located objects are to one another, the stronger their correlation [77]. Spatial autocorrelation allows us to understand the degree to which one object is correlated to other nearby entities and is measured using Moran's I [78]. Two kinds of Moran's I are available, global (GMI) and local (LMI). Due to the possible presence of local spatially autocorrelated observations within an overall random sample distribution [77], we applied both GMI and LMI to analyze the agglomeration features of prefectural IDI concentration.

GMI was used to judge the degree of spatial concentration in prefectural IDI values, as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right) z_j}{\sum_{i=1}^{n} \left(x_i - \overline{x}\right)^2} \quad (5)$$

where n denotes the sample number, while x_i and x_j are IDI values in i and j places, respectively, $\overline{x}$ is the average IDI value, w_{ij} is the spatial weight matrix ($n \times n$), and S_0 is the sum of all elements.

LMI was also used to explore the spatial distribution of "hot spots" and "cold spots", as follows:

$$I_i = \sum w_{ij} Z_i Z_j \tag{6}$$

where x and y denote standardized values of IDI concentrations; thus, when both are positive at a level of significance such that the p value is less than 0.05, IDI concentrations in place i (as well as nearby units) are high and can be referred to as a high-concentration area (HH). In contrast, if x and y are negative then IDI concentrations in place i (as well as nearby units) are low and this region can be referred to as a low-concentration area (LL). Similarly, if x is positive and y is negative, the IDI concentrations of place i are higher than those of neighboring units, a distribution termed a high–low concentration area (HL), while if x is negative and y is positive, the IDI concentrations of place i are lower than those of the units nearby, termed a low–high concentration area (LH). A resultant series of LISA ((Local Indicators of Spatial Association) maps were generated based on these LMI results.

3.2.2. Multiple Linear Regression

In order to better understand the factors influencing the prefectural digital divide in China, we implemented a multiple linear regression to analyze the major drivers between 2001 and 2015. The IDI was used as the dependent variable alongside nine factors used as input variables, namely, the working age population ratio (WAP), level of urbanization (URB), adult literacy rate (ALR), secondary gross enrollment ratio (SER), tertiary gross enrollment ratio(TER), GDP per capita (GDP), disposable income (PIN), and R&D input (RDI), as well as the number of patents granted (PAG).

(1) We utilized a correlation coefficient to analyze relationships between the nine independent variables (Table 3). In this step, we assumed that x_i denotes the x variable in the i-th city, while y_i is one of the variables in the i-th city; the correlation coefficient between the two is therefore as follows:

$$r = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{7}$$

where n denotes the number of cities, while $\overline{x} = \frac{1}{n}\sum\limits_{i=1}^{n} x_i$ denotes the average value of x_i, and $\overline{y} = \frac{1}{n}\sum\limits_{i=1}^{n} y_i$ denotes the average value of y_i. The significance of each correlation coefficient was then assessed using a t test in which the significance level (α) was set at 0.01 and 0.05, respectively.

(2) The initial correlation analysis revealed that some independent variables were highly correlated with another. A component analysis of these nine variables was therefore performed to avoid multicollinearity in the form of a multivariate statistical method that reduces a complex set of variables into a smaller number of components in order to reveal the intrinsic correlation between them and reduce data dimensions. As discussed above, we applied a PCA in this context, with input variables grouped according to their degree of correlation. All input variables were combined using equations and the variance of the dependent variable determined by all inputs was calculated with each linear combination considered to be one component. We selected component factors that had eigenvalues greater than 1 and contained over 70% of the variation of their original counterparts. The results revealed that three principal components with eigenvalues greater than 1 could be extracted from the nine input variables, and that these together can explain 89.91% of the original variation (Table 4).

Table 4. The extracted components for the period between 2001 and 2014.

New Variable	GDP	UIN	RIN	URB	TRA	LIT	EDU	UNI	INNO
F_1	0.964	0.948	0.888	0.302	0.418	0.309	0.356	0.255	−0.103
F_2	0.159	0.131	0.216	0.557	0.352	0.824	0.813	0.835	0.435
F_3	−0.092		0.116	0.408	0.565	−0.014	0.135	0.241	0.657

Table 4 contains the results of component extraction and rotation following PCA and shows the description of original variables using the three component factors extracted in each case. Data show that the first component (F1) mainly reflects levels of economic development (GDP) and income (PIN), while the second (F2) mainly encapsulates the working age population (WAP), education level (ALR, SER, TER), and URB. Finally, the third component (F3) mainly contains the innovation environment (RDI), PAG, and URB. The model used to calculate values for these three component factors is as follows:

$$F_{it} = c_{1it}X_{1t} + c_{2it}X_{2t} + \ldots + c_{9it}X_{9t} + \varepsilon_{it} \quad (8)$$

where F_{it} denotes the i-th component (i = 1, 2, 3) in year t, while X_{1t}, X_{2t}, ... , X_{9t} represent the nine original variables in year t, GDP, PIN, WAP, ALR, SER, TER, RDI, and PAG, respectively, and c_{1it}, c_{2it}, ... , c_{9it} represents the loading of component i on the j-th original variable X_{jt} (i.e., the correlation coefficient between the original variable, X_{jt}, and the component, F_{it}, represented by c_{jit}.

The three components obtained via this analysis were then utilized as new variables and were substituted into the multi-component regression model. The results of this additional model estimation generally fit well with existing data, while at the same time, based on the analysis described above, a further PCA was performed on the data for each year between 2001 and 2015.

4. Analysis and Results

4.1. Temporal Digital Divide Characteristics

The results show that the IDI value in China has risen significantly since 2001. Specifically, IDI values increased from 9.05 in 2001 to 65.09 in 2014 at an annual growth rate of 16.44%. Figure 2 shows that the speed of ICT development nationally can be divided into three different phases, as discussed below.

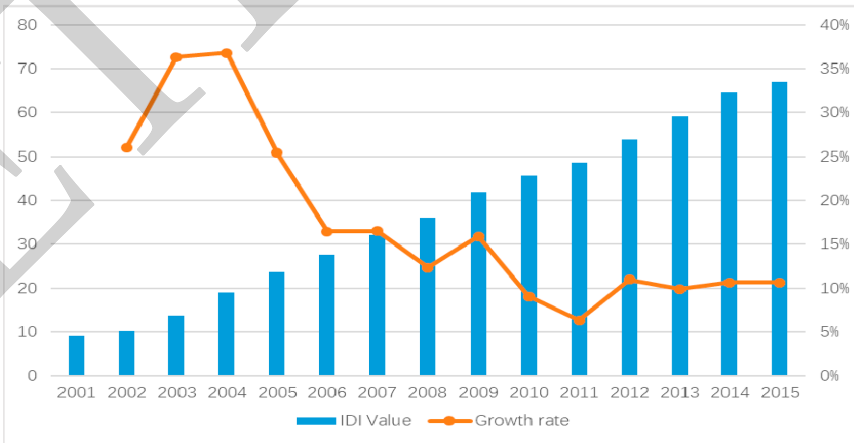


Figure 2. ICT development trends of prefectural cities in China, 2001–2015.

The first phase, between 2001 and 2005, represents the initial ICT development stage, during which the IDI increased from 9.05 to 23.17 at an annual rate of 27.22%. However, because of the relatively late initiation of ICT within China, information technology (IT) applications before 2000 were mainly confined to researchers and highly educated people. Subsequent to this date, the Internet became popular and available to the public owing to rapid ICT developments, and the level of ICT began to increase rapidly. By the end of 2005, China had over 393 million mobile phone and 350 million landline telephone subscribers, while the rate of Internet penetration had increased to 8.5%.

The second phase of technology development, between 2006 and 2009, was characterized by the rapid spread of ICT and an increase in the IDI from 27.62 to 41.87 at an annual rate of 14.88%. The development of ICT in China during this phase was mainly the result of the popularization of Internet applications, the soaring number of CN (i.e., the country code top-level domain for China) websites, and a steady increase in IPV addresses. In particular, the Chinese government's policies for coping with the financial crisis greatly promoted the construction of information infrastructures, as well as the popularization of computers, mobile phones, and other Internet facilities. The number of Chinese citizens using ICTs in 2008 was 298 million, surpassing the United States to encapsulate the largest number of people nationally in the world, while the internet penetration rate reached 22.6%, higher than the global average (21.9%).

The third phase of technology development in China, between 2010 and 2015, was characterized by the overall popularization of ICT and an increase in the IDI from 45.66 to 65.49 at an annual rate of 9.44%. As China transitioned to a fully information-based society, the speed of ICT growth gradually decelerated. Technology development during this stage was mainly the result of growing popularization of the Internet in rural areas, the flourishing of e-commerce, and population-wide participation in online shopping. The number of overall Chinese Internet users, mobile phone subscribers, and individuals connected to the rural Internet had reached 710 million, 656 million, and 191 million, respectively, in 2015.

4.2. Spatial Digital Divide Characteristics

4.2.1. Significant Spatial Differences

Figure 3 reveals an enormous spatial gap in ICT levels between prefecture cities in China. Specifically, IDI values in Shenzhen, Shanghai, Hangzhou, and Beijing were over 120 in 2015, nearly twice the national average, while those in Pingliang and Longnan in Gansu Province, northwest China, Guang'an in Guizhou Province and Chuxiong in Yunnan Province, southwest China, were less than 25, just one-third of the national average. In terms of spatial distribution, the eastern coastal areas of China are characterized by a relatively high ICT level, while densely populated areas in southwest and central China are characterized by a relatively low level of technology use. More specifically, prefectural cities with high IDI values were concentrated in southeastern coastal areas, including Yangtze River and Pearl River deltas, the Bohai Rim and the West Coast Economic Zone of Taiwan Strait. Prefectural cities with low IDIs are mainly concentrated in rural-mountainous regions, including the Wuling, Wumeng, Hengduan, and Liupan mountainous areas, as well as the eastern Qinghai–Tibet Plateau.

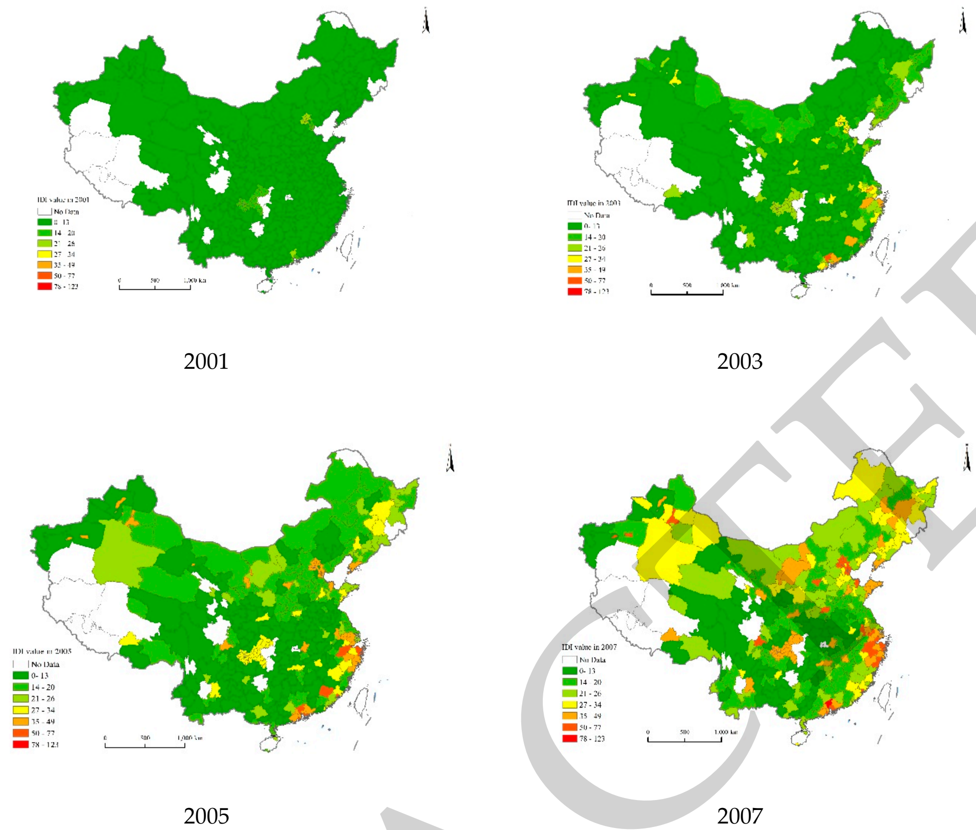


Figure 3. *Cont.*

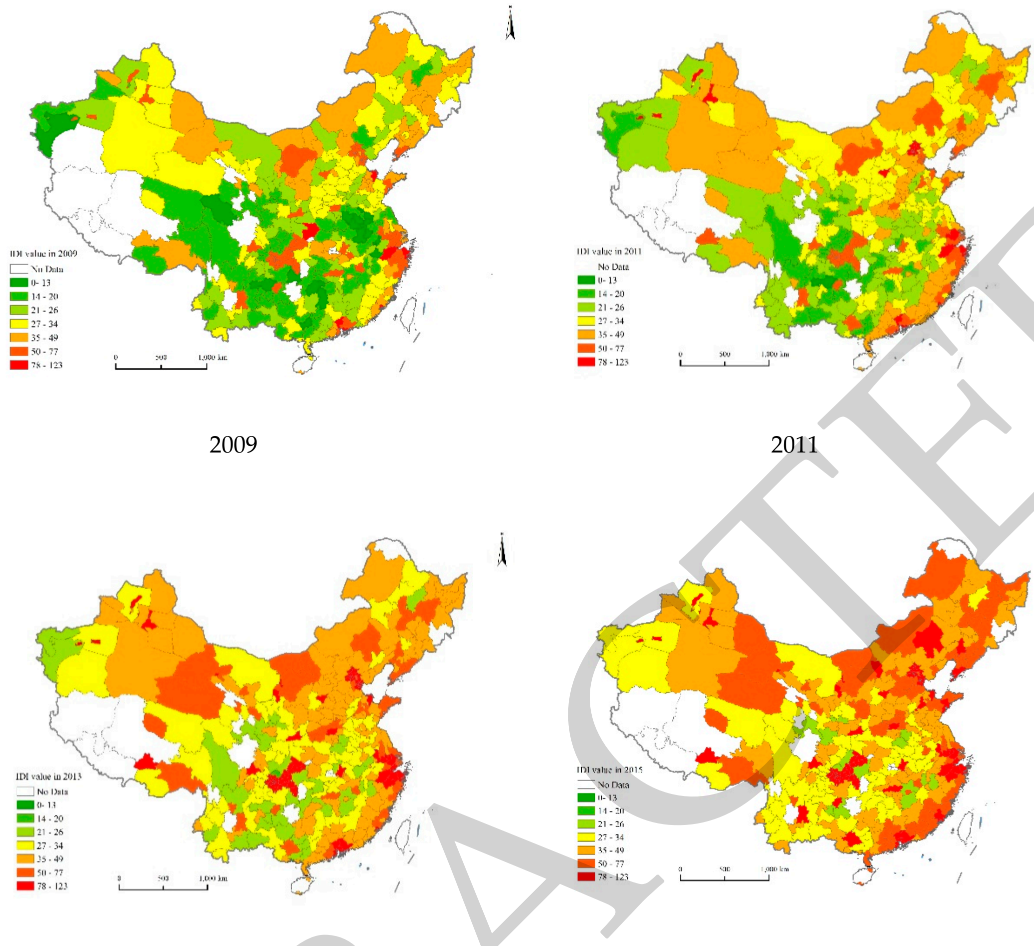


Figure 3. The spatial pattern of prefectural IDI levels in China, 2001–2015.

4.2.2. Narrow of the Digital Divide

Between 2001 and 2015, the IDI value of prefectural cities has improved markedly while the spatial pattern has changed significantly. The largest absolute increases among these cities were seen in Hangzhou and Ningbo in Zhejiang Province, in Suzhou and Wuxi in Jiangsu Province, in Shenzhen in Guandong Province, in Taiyuan in Shanxi Province, in Urumqi in the Xinjiang Autonomous Region, and in Shangha. All of which are characterized by absolute increases in IDI of over 100. The largest relative increases in IDI (greater than 40 times) were seen in the cities of Bayannur and Chifeng in the Inner Mongolia Autonomous Region, in Linzhi and Aba in the Tibet Autonomous Region, and in Guang'an in Sichuan Province, as well as in a number of other prefectural cities. Indeed, as the ICT level in prefectural cities has increased, rankings and spatial patterns of technology use have also undergone relatively large changes. Compared with 2001, data on 2015 show that 158 prefecture-level cities rose in the rankings, while 174 provincial-level cities dropped and just ten remained unchanged. Four prefectural cities were characterized by the highest-ranking increases (all around 200), Bayannur and Chifeng in the Inner Mongolia Autonomous Region, Linzhi in the Tibet Autonomous Region, and Guang'an in Sichuan Province. Cities characterized by the largest falls (all close to 200) in the rankings included Ma'anshan in Anhui Province, Hegang and Daxing'anling in Helongjiang Province, Huaihua in Hunan Province, and Enshi in Hubei Province. The top ten cities with the highest IDI values were all also characterized by relatively large changes, including Hangzhou and Ningbo in Zhejiang Province, Suzhou in Jiangsu Province, and Urumqi in the Xinjiang Autonomous Region, which all entered the top ten in the rankings, while Chongqing, Zhongshan, and Zhuhai in Guangdong Province as well as Tianjin were removed from this category.

From 2001 to 2015, ICT use has spread from eastern coastal areas into central and western regions as well as from core cities into their surrounding areas. In 2001, there is a spatial pattern around a core comprising the Yangtze River and Pearl River deltas, the Bohai Rim, and the Chengdu–Chongqing Economic Zone, while IDI values for cities with a high administrative ranking (e.g., Beijing, Shanghai, Guangzhou, Tianjin, Shenzhen, and Chongqing) also remained relatively high. In contrast, ICT use in China between 2001 and 2005 spread from the core zone encompassed by the Yangtze River and Pearl River deltas and the Bohai Rim, across the entire eastern coastal area before expanding from these latter regions towards the north and west. Eastern coastal areas, as well as northeastern and northwestern regions were characterized by high ICT levels in this period, and the IDI values of provincial capital cities remained significantly elevated compared to the remainder of the provinces. Subsequently, between 2006 and 2009, ICT use continued to expand towards the west and the south, and from provincial capitals to surrounding cities. IDI values at this time were higher in the eastern coastal areas, North China, and Chengdu–Chongqing Region, while densely populated areas in the southwest and center China were characterized by lower IDI values. Finally, between 2010 and 2015, ICT progress gradually moved from core cities with higher administrative ranks toward those lower on this scale. The spatial pattern of IDI values decreased progressively from the eastern region of the country to North China and southwest China, alongside the apparent effect of urban agglomeration. Results show that IDI values have remained consistently higher among groups of cities with higher administrative rankings.

Consistent disparity exists but the digital divide in China has significantly decreased between 2001 and 2015. Data show an absolute IDI difference of 20.0 between Beijing (highest) and Aba (lowest) that corresponds to a relative difference of 25.26 times. In 2014, however, the IDI difference between Shenzhen (highest) and Naqu (lowest) had decreased to 4.49 times, corresponding to a relative difference of 95.47. As revealed by both the IDI relative difference and coefficient of variation (CV), the prefectural digital divide in China has generally tended to decrease. There was an obvious decrease in CV between 2001 and 2010, while subsequent values have slightly increased and gradually stabilized. This phenomenon reflects the fact that China entered a comprehensive IT age from 2010 onwards and ICT progress has been steady with an emphasis on rural areas.

4.3. Spatial ICT Correlation Characteristics

4.3.1. Decline of the Spatial Agglomerations

As shown in Figure 4, GMI remained consistently high, between 0.216 and 0.37 from 2001 to 2014. This reveals that the IDI level of prefectural cities in China is positively spatially correlated, characterized by a linear trend that initially increased and then declined.

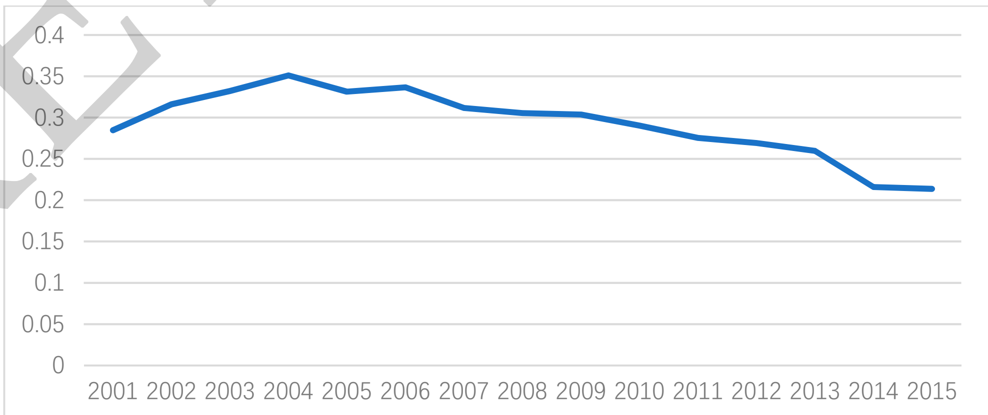


Figure 4. GMI value of prefecture-city ICT levels in China, 2001–2015.

The overall results corroborate the existence of three distinct ICT developmental phases, as discussed above. Between 2001 and 2005, GMI values were characterized by an upward trend with fluctuations (i.e., an initially stable rise followed by a decline). During this phase, the IDI level exhibited a relatively strong spatial correlation at the prefectural level, demonstrating an upward trend with apparent spatial disparity. However, between 2006 and 2009, as ICT use was rapidly spreading, GMI values were characterized by a downward trend amidst fluctuations (i.e., an initial rise followed by a decline). Over this period, ICT values nevertheless retained a relatively strong spatial correlation while also trending downwards with weakened spatial disparity. In contrast, as ICT use became common across China between 2010 and 2015, GMI values continued to decline. At this time, spatial correlation of IDI at the prefectural level decreased annually while spatial disparity also further gradually weakened. Since 2001, prefectural IDI has been characterized by clear spatial correlation while at the same time exhibiting a downward trend. This demonstrates that central hub cities at all levels play a significant driving role, but this influence is declining.

4.3.2. Core Regions of ICT Development

In order to further explore whether local agglomerations exist in ICT development, we performed a combinatorial analysis of LISA map with LMI values to determine spatial correlation patterns for each region.

As shown in Figure 5, IDI hot spots in China in 2001 were mainly located in large metropolitan areas, such as in the Beijing–Tianjin–Hebei, Yangtze River and Pearl River deltas, West Coast Economic Zone of the Taiwan Straits, and Chengdu–Chongqing area. At the same time, sub-hot spots mainly comprised provincial capital cities in the central and western provinces, while cold spots were concentrated in the southwestern region, especially on the Qinghai–Tibet Plateau. Hotspots of IDI became further agglomerated between 2001 and 2005, as southeastern coastal areas including the Yangtze River and Pearl River deltas as well as West Coast Economic Zone of the Taiwan Straits gradually became more prominent zones. Trends in spatial agglomeration within North China were characterized by a gradual decrease over this period, including in Beijing-Tianjin-Hebei and in central-south Liaoning. Cold spots rapidly shrank over this time period and those in Tibet and Xinjiang gradually improved. Over the period between 2006 and 2009, IDI hot spots tended to expand, with the four large metropolitan areas (Yangtze River and Pearl River deltas, Beijing-Tianjin-Hebei, West Coast Economic Zone of the Taiwan Straits) becoming more prominent. Provincial capital cities at this time also developed into agglomeration cores in central and western regions, while cold spots tended to shrink further to distributions within the southwest, central, and northwestern regions of China. Hot-spot areas also decreased between 2010 and 2014, but nevertheless remained concentrated in the four large metropolitan areas. The number of sub-hot spots overall also increased, while sub-hot spots tended to be distributed within major cities in the central and western provinces at this time. Similarly, cold-spot areas shrank further, and tended to be distributed in central and western regions including the eastern edge of the Qinghai–Tibet Plateau, upper reaches of the West River, the Wumeng and Qinba mountains, and the border of West Yunnan.

The results show that the overall number of IDI hotspots in China increased between 2001 and 2014 while the number of cold spots rapidly decreased. In addition, high IDI spatial agglomeration areas are located in eastern coastal cities throughout large metropolitan areas, while low IDI spatial clusters are dispersed in concentrated areas of poverty in central and western China.

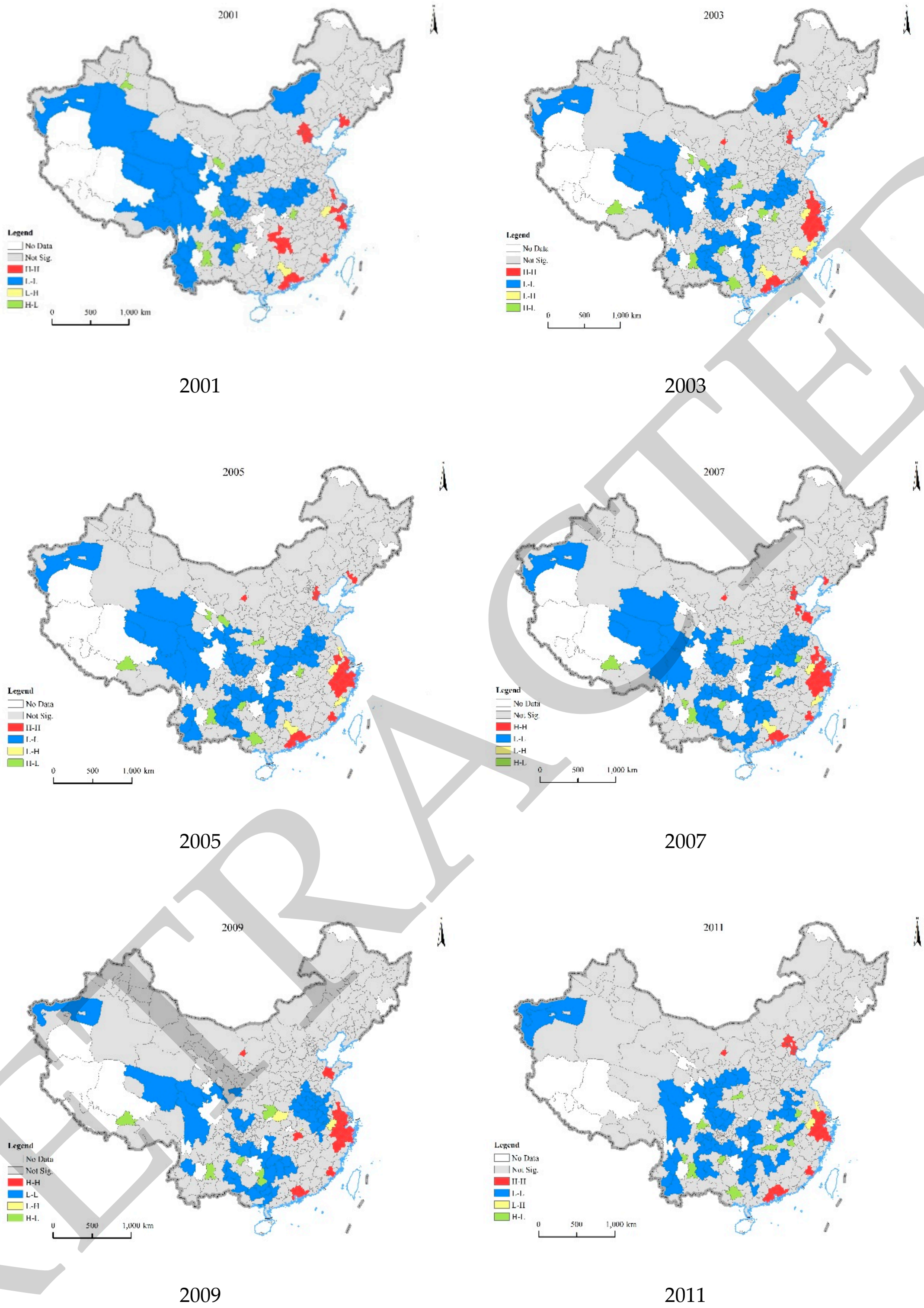
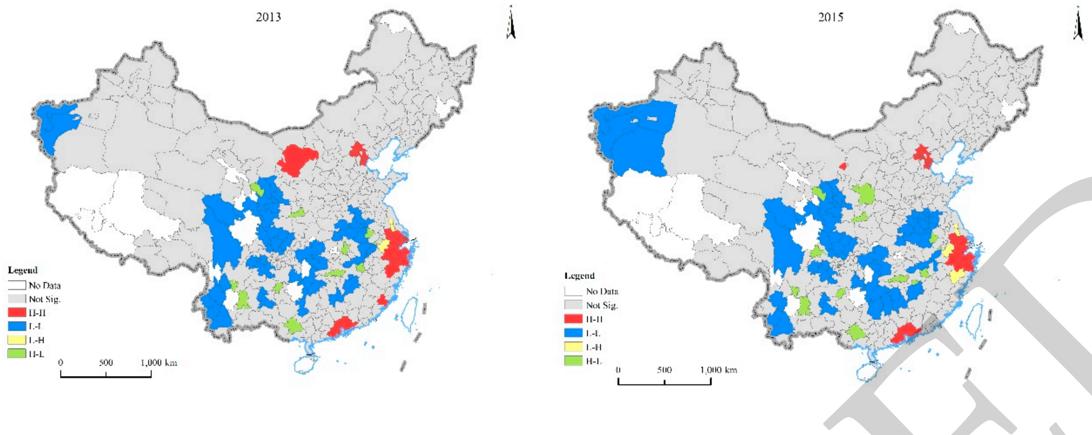


Figure 5. *Cont.*



2013 2015

Figure 5. LISA distribution maps of prefectural IDI values in China, 2001–2015.

5. The Major Factors Influencing Digital Divide

We performed a multiple linear regression analysis to study the major components influencing IDI levels. As shown in Table 5, for data on 2003, 2004, and 2013, the analysis could extract two components with eigenvalues greater than 1; for other years, three components with eigenvalues greater than 1 could be extracted.

Table 5. Coefficients of regression analysis (2001–2014).

	2001	2003	2005	2007	2009	2011	2013	2014	2001–2014
F1	0.629	0.582	0.538	0.508	0.589	0.622 *	0.643 **	0.645 **	0.601
F3	0.593	0.522 **	0.524	0.409	0.371 **	0.306	0.265	0.293	0.374
F2	−0.065 **		0.130	0.136 *	0.088	0.139		0.097 *	0.088 **

Note: *t* test indicating statistical significance of $p < 0.05$; significance at $p = 0.01$ (*); significance at $p = 0.005$ (**).

5.1. Economic Factors

The results show that all the economic factors have exerted relatively significant positive effects on IDI levels but with decreased loading on prefectural spatial differences between 2001 and 2015. Loading from GDP in particular has declined but fluctuated over time, indicating that regional economic development, especially scale and scope, has significantly promoted the development of regional ICT during early stages. However, with ICTs gradually penetrating across the population, the effect of regional economic level on ICT development has gradually decreased. It is clear that regional residential income (PIN) has also been one of the most important factors affecting spatial differences in ICT level, and the loading of this variable has increased over time with fluctuations. During the early stages of ICT development, residential income level exerted a relatively large influence on spatial differences in regional ICT, while the per capita disposable income of urban residents in this context has been the most important factor. As ICTs have become rapidly more popular, however, the impact of residential income level has tended to decline. By the point of full stage ICT penetration, the impact of residential income on these technology levels gradually increased again, especially as the effect of rural residential income gradually became more prominent.

5.2. Educational Factors

Educational factors also exerted significant positive influences on spatial differences in ICT levels in prefectural cities between 2001 and 2015, although this loading effect declined over time. In particular, the impact exerted by the tertiary gross enrollment ratio (TER) was characterized by a relatively marked decline, while the influence of the secondary gross enrollment ratio (SER) on the development of these technologies also declined slightly, albeit with fluctuations. In contrast, the impact of the ALR on

ICT development increased but fluctuated over the time period of this study. These results suggest that higher education (TER) was a major driving force during the early stage of ICT development (i.e., spatial discrepancies in these technologies were more sensitive to the proportion of the population with a higher level of education). Subsequently, as ICTs penetrated the general Chinese population, the influence of TER on their development gradually declined, while the effect of SER gradually increased (i.e., the proportion of the population with a secondary level education gradually replaced the influence of the population proportion with a higher educational level and developed into a more important factor in ICT penetration). Changes in the impact of elementary education have tended to conform to the opposite trend. As ICTs have continuously progressed throughout the population, especially in light of the popularity of smartphones and the increasing utility rates of mobile internet from these devices, elementary education (ALR) is now the fundamental threshold enabling access to this Internet, and has exerted more and more impact on the development of these technologies. At the final stage of full ICT penetration (2014), ALR gradually replaced SER and TER to become an important factor controlling the spatial ICT discrepancies.

5.3. Other Factors

Other factors have not exerted significant influence on spatial ICT differences. Specifically, although the proportion of urban population (URB) has exerted a positive influence on spatial ICT level differences between prefectural cities, its influence overall has tended to decline albeit amid fluctuations. Data show that during the early developmental stages of ICT, URB did exert a significant influence on the growth of these technologies but that this effect has gradually declined as their penetration has spread. Indeed, the influence of URB on spatial ICT differences markedly declined subsequent to 2010; this result further indicates that once these technologies had become widespread and popular, especially in rural areas, the influence URB on spatial differences then tended towards zero.

We also found that the R&D input per capita (RDI) was not a prominent factor influencing spatial ICT differences. Prior to 2007, RDI did exert a weak positive influence on these spatial differences, however, indicating that the innovation output of a region was important to ICT development. This impact rapidly declined after 2007 with a very low, even negative, CV indicating that after the financial crisis, RDI exerted almost no effect on Chinese ICT development.

Finally, data show that the proportion of working age population (WAP) has also exerted little effect on spatial ICT differences; only during the financial crisis (between 2008 and 2010) was it the case that foreign trade exhibited a relatively positive influence on Chinese ICT spatial differences. This variable has exerted a weak influence on the development of these technologies both nationally and regionally at all other times.

6. Conclusions and Discussion

6.1. Conclusions

Since the start of the 21st century, ICT development in China has accelerated and become one of the biggest ICT markets in the world. At the same time, ICT access and use inequality have emerged as a consequence, which has loomed as a sustainable development issue. In this study, we developed and validated a conceptual model for the prefectural digital divide in China, which covers the first- and second-order digital divides, and explored the major influential factors of the prefectural digital divide using a multiple linear regression model.

The findings indicate that the overall level of ICTs in China has been significantly enhanced between 2001 and 2015. On the one hand, prefectural IDI level in China have exhibited drastic differences over time, and gradually decrease along an east-to-west transect. Cities characterized by high administrative levels tend to have relatively high IDI values. Between 2001 and 2014, ICT development has spread from eastern coastal areas into central and western regions, and from core cities into their surrounding areas. These developments have significantly narrowed the Chinese digital divide. On the other hand, the spatial autocorrelation analysis reveals that high IDI regions tend to be large urban agglomerations in eastern coastal areas of China, while low IDI counterparts are mainly found in regions with high levels of poverty in central and western parts of the country. This developmental trend in ICT spatial agglomeration has gradually decreased over time.

Multivariate linear regression analysis shows that ICT is closely correlated with the economic and educational levels of development within a region. Thus, the residential income (PIN), tertiary gross enrollment ratio (TER), and the proportion of urban population (URB) variables all exerted a relatively large influence during the initial ICT developmental phase from 2001 to 2005. Subsequently, however, during the second rapid ICT spreading phase from 2006 to 2009, secondary gross enrollment ratio (SER) and GDP per capita (GDP) tended to exert more significant effects on this phenomenon. Finally, during the phase of overall ICT popularization subsequent to 2010, residential income (PIN), and adult literacy rate (ALR) became the dominant factors affecting spatial differences in these technologies.

6.2. Discussion

The prefectural digital divide is the consequence of the accumulation of numerous factors within China over many cycles. Indeed, the spatiotemporal evolutionary patterns highlighted by this study represent the local embodiment of national economic development, including ICT. Although we analyzed the digital divide in smaller geographic units than previous studies, there are still some sample limitations. There are 344 prefecture-level cities in China, but we could only measure the digital divide for 302 of them and analyze a sample of 291 prefectural cities for its drivers. For the remaining 53 prefectures, which are mostly autonomous prefectures, there was a lack of data. Because most comprehensive national geographic or statistical coverage in China is undertaken at the provincial level, it was extremely difficult to collect data and materials for the prefecture-level cities.

The results indicate that there have been many policy measures undertaken to promote ICT development and reduce the regional digital divide. Initially, socio-economic problems, rather than institutions, R&D and innovation aspects, have to be solved to improve ICT access and use in the region. The association of resident incomes and urban locations with ICT use, affirming central government policies to improve urbanization rates and resident incomes, to stimulate positive results from ICT use. Furthermore, we suggest that the central government further promotes the popularization of nine-year compulsory education (grade 1–9) to ensure citizens have basic knowledge and skills regarding ICT use.

For researchers, this study provides some novel findings on the digital divide correlates for the world's largest nation. As a result of the advent of the information age, the development of ICTs in China and developing countries will have far-reaching spatial significance on social sustainable development. In light of current trends, a spatial analytical perspective on the digital divide in China, the impact of this phenomenon on regional development patterns, the future expansion of rural ICTs, and the growth of e-commerce are all topics that are worth future exploration and investigation.

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