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Geography, Ethnicity and Regional Inequality in Guangxi Zhuang Autonomous Region, China

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Abstract This paper analyzes regional inequality in Western China through a case study of Guangxi Zhuang Autonomous Region from 1989 to 2012. We have found a recent trend of increasing county-level inequality, in which the distribution of regional inequality has changed from a single peak to a bimodal pattern. Based on the multi-mechanism framework, we have revealed that geographic environment and ethnic characteristics have had a large impact on the economic development of Guangxi. Spatiality, investment and industrialization play an additional important role in regional development; meanwhile, globalization and decentralization play a minor role. Building on the semiparametric geoadditive models, our investigation detects nonlinear

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relationships between geography, ethnicity and local development. We then assess the relative performance of infrastructure and market potential to control for unobserved spatial heterogeneity.

Keywords Regional inequality · Geographic environment · Ethnicity · Guangxi · Semiparametric geoadditive models

Introduction

China's economy has maintained rapid growth since the reform and opening-up policy was initiated in 1978. This growth has been accompanied by sharp rises in inequality, as government policies have aimed at the concentrated development of coastal regions (Anwar and Sun 2012; Appleton et al. 2014; Yue et al. 2014). These policies have led to serious problems of imbalanced growth and intensified social injustice in less-developed regions, especially poor ethnic regions (Wei and Fang 2006; Luo et al. 2009; Xing et al. 2009; Howell and Fan 2011; Wu and Song 2014). The government policy for less developed regions in China, such as the Western Development Strategy, is spatially uneven and favors key cities in western provinces. Many rural areas are still troubled by persistent poverty and underdevelopment. For example, higher education reforms including decentralization and commercialization of higher education intensify social injustice, which have disadvantaged poor people in impoverished regions but created relatively more opportunities for the advantaged groups and regions (Yao et al. 2010). Regional inequality, which has always been an important policy issue in China, is intertwined with economic development, ethnic relations, political unity and social stability (Wang and Hu 1999). In fact, many provinces in Western China have complained about the preferential policies addressing the coastal region and the consequences of the widening regional gap. In reaction to this, these provinces have actively lobbied the central government to grant similar policies to the western region (Yang 1997). More importantly, these denunciations of expanding regional inequality have increasingly coincided with concerns about political stability and national unity (Tian 2004).

Using data of 89 counties in the Guangxi Zhuang Autonomous Region in Western China, we contribute to the existing literature by 1) analyzing intra-provincial economic inequality and the mechanisms underlying poor regions in China, 2) assessing the driving forces underlying regional inequality through geography, environment and ethnicity, and 3) assessing the presence of nonlinearities in the relationship between regional inequality and its determinants. Using smooth functions, we employ a semiparametric model to identify and capture the possible nonlinear effects of exogenous variables in regional inequality. We adopt a geoadditive component, a smooth interaction, which controls unobserved spatial heterogeneity. Ordinary Least Squares (OLS), a Spatial Lag Model (SLM), and a Geographically Weighted Regression (GWR) are conducted to compare how well global and local regressions explain the development mechanisms.

This paper is organized as follows. After an introduction to our motivation and research methods, we analyze multiscalar patterns of spatial inequality at the regional, municipality and county levels in Guangxi. A detailed investigation is conducted on the spatial-temporal dynamics of regional inequality among 89 counties and cities with both traditional and spatial Markov chains. We then use the multi-mechanism framework of geography, environment and ethnicity to examine the determinants of regional inequality. The paper closes with a research plan and policy suggestions for the regional development of poor regions in China.

Motivation and Research Setting

Motivation

Work on provincial China has primarily addressed developed eastern provinces, such as Zhejiang (Ye and Wei 2005; Yue et al. 2014), Beijing (Yu and Wei 2008), Jiangsu (Wei et al. 2011), and Guangdong (Liao and Wei 2012; Lei 2014). In contrast, there are fewer studies of intra-provincial inequality and related policy outcomes in less-developed regions (Wei and Fang 2006). Most existing literature on the economic inequality of poor provinces has focused on descriptive analysis and theoretical discussion, and empirical investigations of the mechanisms of inequality are lacking (Cao 2010). Some scholars describe and examine the extent of regional inequality (Aarvik 2005; Han and Qin 2005; Veeck et al. 2006; Cappelletti 2016), while others analyze the driving forces (McNally 2004; Fischer 2005; Pannell and Schmidt 2006; Wei and Fang 2006). We use the Guangxi Zhuang Autonomous Region as a case to reveal the driving forces behind uneven regional development in China's poorer regions and substantiate our findings through empirical evidence and robust methods.

Most previous studies assess the impacts of socioeconomic factors (such as FDI, education, urbanization, economic structure, globalization and liberalization, marketization and decentralization, creativity, capital, and openness) and policies (such as financial policies, environmental policies, industrial development strategy, and labor market reform) on regional inequality considering the effects of globalization and liberalization in the context of economic transition in China. However, those factors cannot fully explain the economic inequalities of poorer areas. Hence, environmental factors (such as terrain, climate and water resources) also must be investigated (Gallup et al. 1999; Wei and Fang 2006; Mendoza and Rosas 2012; Auer 2013; Brezis and Verdier 2014; Li and Fang 2014). Meanwhile, ethnic differences in economic performance have also been noted (Alesina et al. 2013). China's western poor regions are challenged by ecological vulnerability and poverty in relation to ethnicity (Lahtinen 2009). For example, income disparity exists along the lines of ethnicity and is most pronounced for Uyghur minorities (Howell 2013). In addition, the core-periphery pattern tends to exacerbate intra-provincial inequality in Western China, and it has strong geographic foundations that are difficult to overcome (Wei and Fang 2006; Cao 2010; Li and Wei 2014). The stony desertification of the karst mountainous regions has become a considerable ecological issue leading to poverty in Southwest China (CAS 2003). Therefore, the effects of environment and ethnic issues on regional development need to be investigated for poor areas. To assess the mechanism of regional inequality in less-developed regions, we take environment and ethnicity into account in addition to spatiality, policies and socioeconomic factors.

Many previous studies disregard the existence of nonlinearities in the relationship between determinants and regional inequality, though it is widely recognized that economic growth is characterized by strong nonlinearities (Henderson et al. 2012). Some authors (e.g., Mendoza and Rosas 2012; Auer 2013; Policardo et al. 2016; Wu and Tam 2015) allow for nonlinearities by introducing quadratic terms. Nonlinearities can be better clarified in a semiparametric framework, where the partial effects of univariate terms are estimated by smooth functions (Basile et al. 2013). In addition, a part of the unobserved spatial heterogeneity can be captured by GWR when specifying the regional economic inequality model in China (Wei and Ye 2009; Wei et al. 2011). However, GWR based on the linear functional form (Helbich and Griffith 2016) has limitations due to the nonlinearities among certain variables. The GWR model is also inadequate for many socioeconomic variables with global effects (e.g., taxes, interest rate and date), which are independent of individual localization (Geniaux and Napoléone 2008).

Research Setting: Guangxi Zhuang Autonomous Region

As shown in Fig. 1, the Guangxi Zhuang Autonomous Region is located at the juncture of Eastern, Central and Western China and is also the only region that connects to ASEAN (Association of Southeast Asian Nations). In 2012, Guangxi produced 1303.51 billion Yuan of GDP, which only accounted for 2.51% of China's GDP, and had a per capita GDP of 27.95 thousand Yuan, 72.75% of the national average. As one of China's five autonomous regions, the region has over 20 million Zhuang, the largest

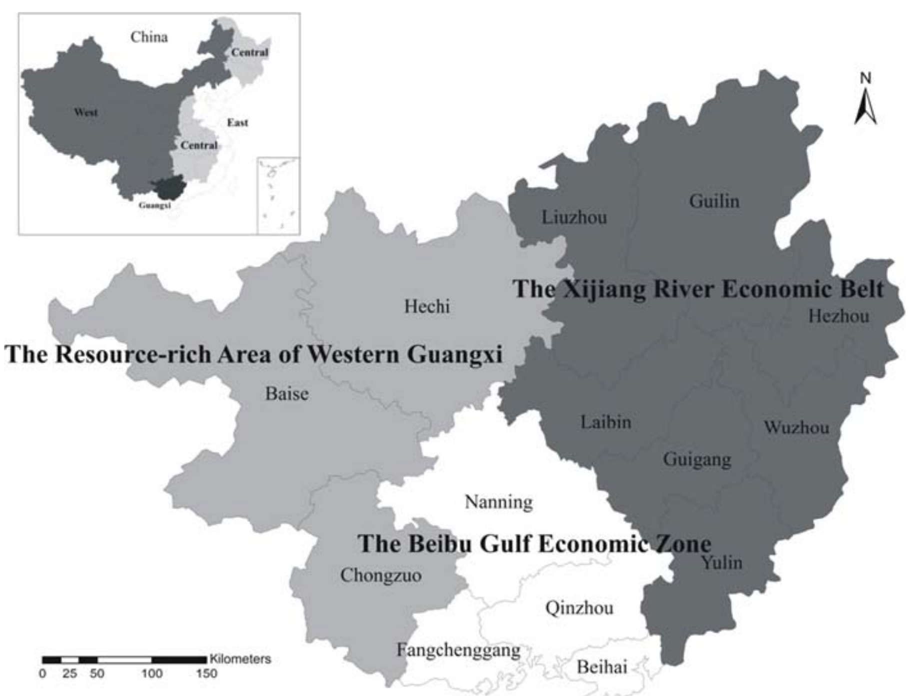

Fig. 1 Location of Guangxi and regional divisions

ethnic minority of China. Guangxi is also known for its environmental problems and rocky land desertification. Karst landforms are widespread in this region, accounting for 67% of the total area and, in turn, have exacerbated the poverty level in the rural areas (Liu et al. 2008). As an old revolutionary base, ethnic minority region, border province and poor area, the development of Guangxi and its intra-provincial inequality are therefore significant subjects for investigation.

According to the administrative structure of Guangxi in 2012, there are 14 municipalities and 89 spatial units at the county level, including 14 urban districts (city) and 75 counties (rural counties and county-level cities) (Fig. 1). Guangxi is composed of three regions including the Beibu Gulf Economic Zone (BGEZ), the Xijiang River Economic Belt (XREB) and the resource-rich area of Western Guangxi (WG) (Fig. 1). The BGEZ is becoming a core area in Guangxi with the promotion of national policies. In 2012, with a population of 12.38 million (26.45% of the province), the BGEZ region produced 33.15% of Guangxi's total GDP and attracted over half of the FDI in the province.

Methodology

We use the Theil index and decompose it into multiple scales with consideration of the hierarchical structure of a province. In addition, kernel density estimation is applied to estimate changes in the distribution of relative GDP per capita (GDPPC) (the ratio of GDPPC in each county compared to the mean value in the province). We will examine Moran's I (both global and local) and employ spatial Markov chain analysis to examine the probability of regional convergence, divergence and polarization. In this study, the GDPPC data are categorized into four groups (rich, developed, less developed and poor) according to the World Bank's regional economic classification methods and standards.

If a county's GDPPC is 75% lower than the average level of the province, it is considered to be poor; between 75% and 100% is less developed; between 100% and 150% is developed; and higher than 150% is rich.

To further understand regional inequality, the multi-mechanism framework is used to examine the driving forces behind uneven regional development. We employ four models: OLS, SLD, GWR, and PS-SLX (the Penalized-Spline Spatial in X-variable model). The semiparametric geoadditive model can simultaneously address three issues of spatial dependence, unobserved spatial heterogeneity and nonlinearities (Basile et al. 2013). Formally, its general form is expressed as

$$y_i = x_i^{*'}\beta^* + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + f_4(x_{1i}) + \ldots + h(no_i, e_i) + \varepsilon_i, \quad \varepsilon_i \sim iidN\left(0, \sigma_\varepsilon^2\right), \\ i = 1, \ldots, n$$

where y_i refers to the dependent variable (GDPPC) in county i. $x_i^{*'}\beta^*$ is the linear predictor for the parametric component, with β* being the coefficient of explanatory variables. $f_k(.)$ are unknown smooth functions, capturing the nonlinear effects of exogenous variables. The independent variables entering the model parametrically or non-parametrically could be chosen through theoretical priors or as the result of model specification tests (Kneib et al. 2009). $f_4(x_{1i})l_i$ is a varying coefficient term, where l_i is either a continuous or a binary covariate. The term h (no_i, e_i) is a smooth spatial trend surface (no_i is latitude, and e_i is longitude) that allows us take into account unobserved spatial heterogeneity. Finally, ε_i are iid normally distributed random shocks.

This model rules out spatial interaction effects. Spatial lags of the exogenous (X) variables can be introduced into the above model to capture the local spatial spillovers. This model is termed PS-SLX (Basile et al. 2014).

$$y_i = x_i^{*'} \beta^* + f_k(x_i) + \delta \sum_{j=1}^{n} w_{ij} x_j^{*'} + g_k\left(\sum_{j=1}^{n} w_{ij} x_j\right) + h(no_i, e_i) + \varepsilon_i$$

$\varepsilon_i \sim iidN\left(0, \sigma_\varepsilon^2\right)$, $i = 1, \ldots, n$.

The term w_{ij} is the element of a spatial weights matrix W_n, $\beta \sum_{j=1}^{n} w_{ij} x_j^{*'}$ is the spatial lag of the independent variable, and δ is the spatial spillover parameter.

The estimators for the semiparametric models include the penalized least squares (PLS) method and a generalized cross validation (GCV) score minimization process (Basile et al. 2014). OLS is used to estimate the parametric model in the PS-SLX specification, while the semiparametric model is estimated by restricted maximum likelihood (REML). This eliminates the fixed effects of the linear combinations of the dependent variable (McCulloch et al. 2008) and can solve the problem of reduction in the degrees of freedom. We also use the GCV method, which appears to be superior (Wood 2011).

Based on our review of the existing literature on regional development and work on Western China, as well as on the multi-mechanism framework that conceptualizes Guangxi's regional inequality as the determinant of environment, ethnicity, policy, spatiality and socio-economy, we have identified a number of exploratory variables as follows:

1. *Geographic and environmental factors*

The elevation difference between the highest and lowest values (LNELE), the slope (SLOPE), and the share of an area with the slope over 10° (5°) in the total area are employed to investigate the impact of physical geographic characteristics on regional development. The karst area accounts for 35.2% of Guangxi and covers ten cities (Liu et al. 2008). We use the stony desertification (the share of regions characterized by severe stony desertification in total area) to investigate whether regional development is restricted by environmental factors.

2. *Ethnic factors*

Given the increase of the income gap between the minority and majority population (Cao 2010; Howell and Fan 2011; Wu and Song 2014), ethnic stratification has received growing attention. Our research employs the share of the minority population in the total population (MP) to investigate the impact of national structure on regional development. Ethnic Minority Autonomous County (EMAC) is chosen as a dummy variable to examine the effect of ethnicity in regional development. If the spatial unit at the county level is an EMAC, it is coded by 1; otherwise, it receives a 0. As one of the five ethnic minority autonomous regions in China, Guangxi has the largest ethnic minority population and with 12 ethnic groups long-dwelling. These ethnic minorities located in different areas with different performance. We use the statistics of the entire ethnic population because there is no data for each ethnic population.

3. *Policy and spatial factors*

Economic development zones (EDZ) are used to reflect the impact of national strategies and regional policies on regional development (Li and Fang 2014). We also select a dummy variable to capture the role of EDZ in regional inequality. If a county is included in a preferential policy, this county is marked with 1; otherwise, it receives a 0. The nearest distance to the capital and major industrial city (LNDISTANCE), Liuzhou city, from each county's center, is used to explore the influence of location factor in regional development.

4. *Socioeconomic factors*

Fixed asset investment per capita (LNFIXPC) is selected to represent whether regional development is driven by investments. Per capita FDI (LNFDIPC)[1] is used to reflect the extent and impact of globalization on regional development. The share of the output value of secondary industry in GDP (IND) is employed to investigate whether industrialization has intensified regional inequality. The decentralization process (DEC) is captured by the ratio of local budgetary spending per capita to the provincial government's budgetary spending per capita; this mainly reflects the degree of fiscal decentralization and the shift of power from upper-level governments to local governments (Hao and Wei 2010). Road density (ROADDEN) is often representative of the effect of infrastructure on regional development and is calculated based on the lengths of the routes and the county area. Greater population density (POPDEN) may provide a sufficient labor market and greater product consumption, with potential effects on regional inequality (Lessmann and Seidel 2015).

This study adopts the most commonly used indicator of regional development status, per capita GDP (GDPPC), from 1989 to 2012. The municipality-level (14 municipalities) and county-level (89 counties) data acquired in this paper include geographic, environmental, ethnic, spatial and socioeconomic data as well as policy documents. Considering that the comprehensive price index and inflation rate are constantly changing across the different periods, the GDP data of each year are converted to real data using CPI, with 1978 as the baseline. The local fiscal expenditure per capita at the county level is converted in the same way. In addition, this paper employs investment flow data and the perpetual inventory method to estimate capital stock due to a lack of capital stock data. The GIS maps (shape files), with boundary files of Guangxi province down to the county level, were downloaded from the China Data Center.

[1] Due to the lack of FDI statistical data, gross output value of industrial enterprises above the designated size of Hong Kong, Macao, Taiwan and other countries to the total population in each county is used to reflect the extent and impact of globalization.

Multiscalar Patterns of Regional Inequality

In this section, a multi-scale decomposition analysis is undertaken to portray a holistic scenario for the evolution of regional inequality in Guangxi over the past two decades. Fig. 2 shows that the regional inequality in Guangxi is sensitive to geographic scale. The average numbers for inter-county inequality, inter-municipality inequality and interregional inequality are 0.087, 0.024 and 0.007, respectively. Regional inequality is more significant at finer spatial units. Figure 2 reflects a similar trend of upward inequality with fluctuation before the 2000s at the county and municipality scales in Guangxi during the study period. By contrast, interregional inequality displays a consistently steadier trend with a slight increase in recent years.

Inter-county inequality is significantly higher, most likely because we take the municipal districts into consideration when selecting the counties as the geographic scale of research. This is because the GDP per capita of municipal districts is significantly higher than that of other rural counties. The differences among the three regions look relatively small, which is likely attributable to the overall backward development level of Guangxi and the lack of a strong growth pole. However, the intra-regional inequalities are significantly higher (Fig. 3). The average numbers for the inter-county inequality of BGEZ, XREB and WG are 0.082, 0.088 and 0.054, respectively. Figure 3 reflects a similar trend of rising inequality in BGEZ and XREB during the study period. By comparison, the inter-county inequality of WG fluctuates slightly. Notably, WG's inequality was significantly lower than that of the other two regions because development in this region lags behind. GX is the poverty center and peripheral area of Guangxi and is composed of many ethnic minority autonomous counties with slow economic growth and rocky desertification in the mountains. The rise of regional inequality is closely related to the rapid development of those counties with rich mineral resources because of the strategy of "western development" and liang qu yi dai ("two districts and one belt").

To explore the relationship between the scale of the analysis and inequality in Guangxi, we decompose the overall inter-county inequality into the inequalities

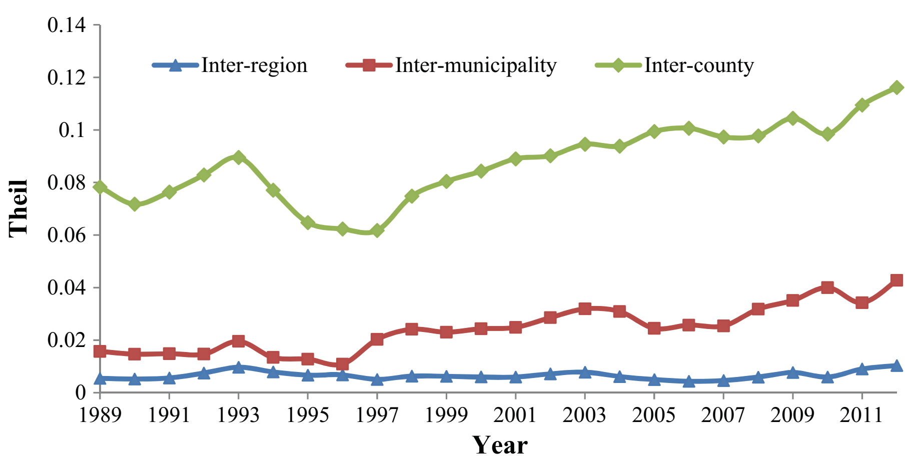

Fig. 2 Regional inequalities at different scales in Guangxi, 1989–2012: Theil index

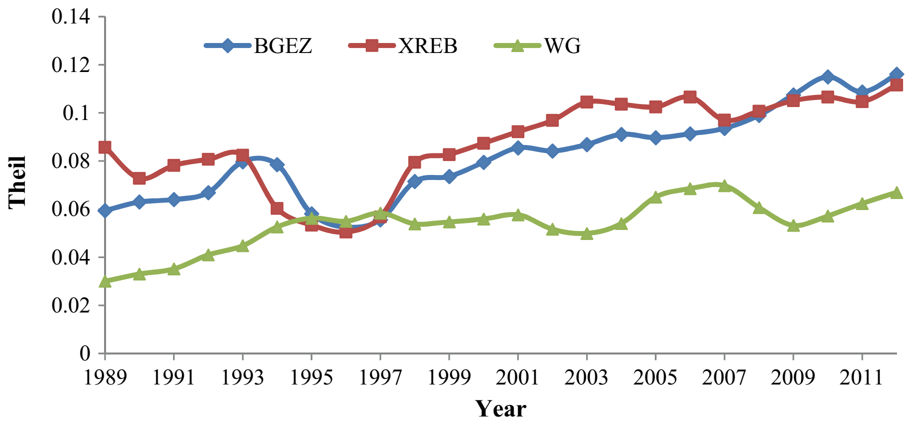

Fig. 3 Regional inequalities of inter-county at region scale in Guangxi, 1989–2012: Theil index. *Note*: BGEZ: the Beibu Gulf Economic Zone, XREB: the Xijiang River Economic Belt; WG: the resource-rich area of Western Guangxi

between and the inequalities within the BGEZ, XREB and WG counties; this latter consists of the inequality within and between municipalities. As illustrated in Fig. 4, in the composition of overall inter-county inequality, the contribution of inequality among regions increased slightly from 6.30% in 1989 to 7.65% in 2012, while inequality among municipalities increased from 18.64% in 1989 to 34.19% in 2012, and inequality within municipality counties decreased from 75.06% in 1989 to 58.16% in 2012. In short, the proceeding analysis finds that the uneven economic development is sensitive to the time dimension and the geographic scale. It is also affected by the inequalities

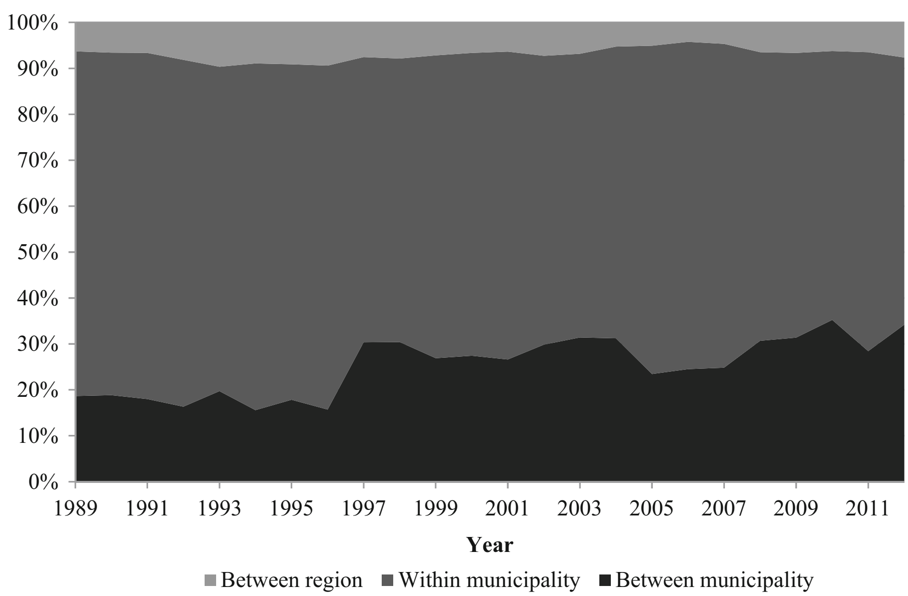

Fig. 4 Theil decomposition of inter-county inequality in Guangxi, 1989–2012

within regions, especially inter-county inequality within municipalities, as these are still the main source of uneven development.

Spatial-Temporal Dynamics of Regional Disparity

The curve plots display an apparently skewed distribution of the relative GDPPC (Fig. 5). First, more counties are below the average GDPPC. Second, the distribution shape of the relative GDPPC in Guangxi has shifted from a single peak to a double peak. Third, compared with the year 1989, the kernel density value of the curve in 2000 and 2012 declines from 2.0 to 1.0 and 0.85, reflecting a decreasing concentration of wealth at the county level.

The dialog numbers are higher in the Markov chain tables, which means that each category tends to remain at the current level. However, the transition frequency between different groups is low (Table 1). This shows that it is very difficult for a county to leapfrog, indicating a relatively stable regional development system.

The traditional Markov approach cannot reveal the spatial characteristics behind the evolution of regional development, as it ignores spatial interaction (Anselin 2005; Rey 2009), but spatial Markov chain analysis can solve this problem. The analysis results are shown in Table 2. First, as shown in Table 1, the poorest counties in general have a tendency of 6.3% to move upward. However, if a poor county has poor neighbors, the tendency to move upward will drop to 2.7%. Meanwhile, if its neighbors are rich, the tendency to move up will increase to 37.5% (Table 2). Second, a developed county has a 10.3% tendency to move downward despite its neighborhood status. However, if its neighbor is less developed, the target county has a higher chance (14.8%) of becoming a less developed county. Third, comparing the two tables, we find that the neighborhood effect does not significantly apply to rich counties. Moreover, rich counties are more influenced by their own development conditions (such as the geographic location)

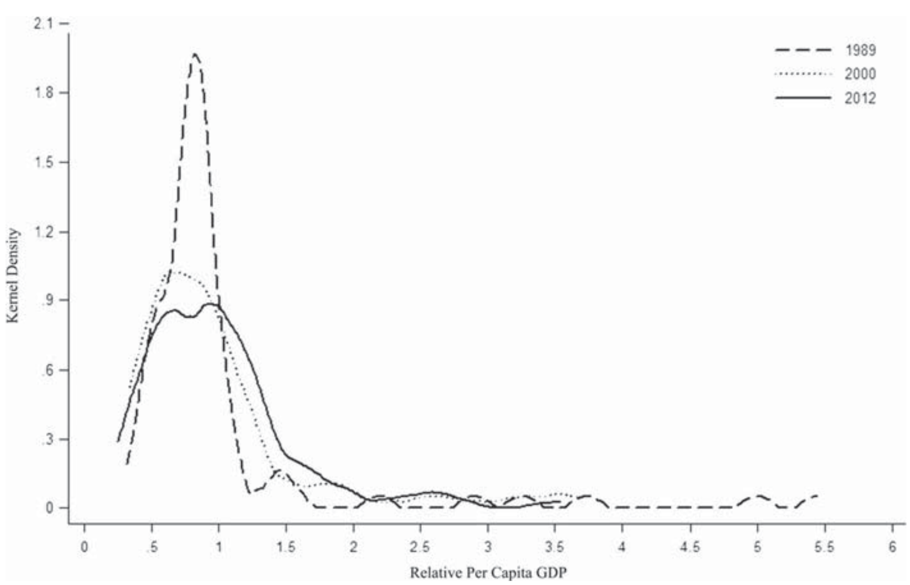

Fig. 5 Kernel densities of relative per capita GDP at the county level, 1989, 2000, 2012

Table 1 Markov-chain transitional matrices for county level GDP per capita in Guangxi, 1989–2012

	N	P(<75%)	L(<100%)	D(<150%)	R(>150%)
1989-2012P	810	0.936	0.063	0.001	0.000
L	560	0.098	0.775	0.123	0.004
D	447	0.002	0.103	0.828	0.067
R	230	0.004	0.009	0.109	0.878
1989-1999P	320	0.922	0.075	0.003	0.000
L	317	0.104	0.782	0.107	0.006
D	159	0.006	0.126	0.761	0.107
R	94	0.011	0.000	0.149	0.840
2000-2012P	490	0.945	0.055	0.000	0.000
L	243	0.091	0.765	0.144	0.000
D	288	0.000	0.090	0.865	0.045
R	136	0.000	0.015	0.081	0.904

P poor, *L* less developed, *D* developed, *R* rich, *N* refers to the numbers of transitions

and macro context (such as a national strategy of "western development"). In addition, the spatial Markov chain provides a spatial explanation for the "club convergence" phenomenon in Guangxi. The development of a county is affected by the economic conditions of its neighbor, and the transfer direction of regions is often consistent with that of the neighboring counties. If a county is adjacent to poorer counties, it will be negatively affected; however, if it has richer neighbors, the probability of upward movement will increase.

Figure 6 provides that the number of those moving upward during the period of 2000–2012 is slightly more than that during the period of 1989–1999 and the amount of counties with downward movement has not changed although more than half of the counties remains stable at both stages. Counties with upward movement are distributed

Table 2 Spatial Markov-chain transition matrix for county level GDP per capita in Guangxi, 1989–2012

2012 Spatial lag	1989	N	P	L	D	R
P	P	297	0.973	0.027	0.000	0.000
	L	24	0.250	0.667	0.083	0.000
	D	34	0.000	0.029	0.765	0.206
	R	44	0.000	0.000	0.205	0.795
L	P	344	0.942	0.055	0.003	0.000
	L	272	0.081	0.786	0.129	0.004
	D	149	0.007	0.148	0.751	0.094
	R	81	0.012	0.012	0.086	0.890
D	P	161	0.863	0.137	0.000	0.000
	L	233	0.112	0.794	0.094	0.000
	D	218	0.000	0.092	0.881	0.027
	R	74	0.000	0.000	0.081	0.919
R	P	8	0.625	0.375	0.000	0.000
	L	30	0.033	0.633	0.300	0.034
	D	47	0.000	0.085	0.851	0.064
	R	31	0.000	0.032	0.097	0.871

P Poor, *L* Less developed, *D* Developed, *R* RICH, *N* refers to the numbers of transitions

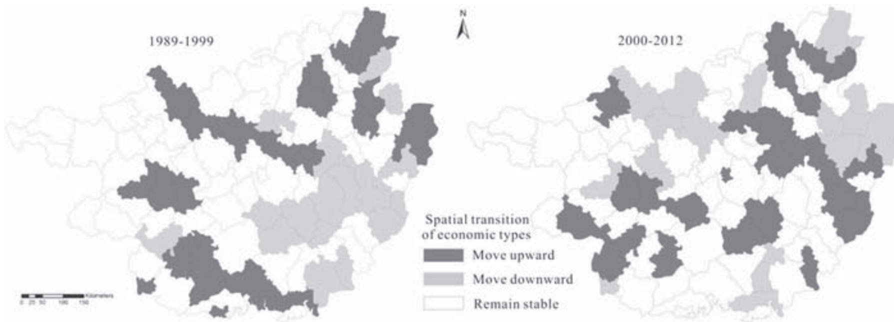

Fig. 6 Spatial patterns of class transition for counties and neighbors per capita GDP in Guangxi, 1989–2012

around Liuzhou city, Guilin city, Wuzhou city and Chongzuo city while counties with downward movement are located in Hezhou city and Hechi city between 2000 and 2012 in Fig. 6.

Figure 7 provides more detail about the possible association between the direction and probability of transitions and the neighborhood context in space. It can be observed that counties with upward and downward movement are always adjacent to regions demonstrating the same change. Regional convergence becomes more evident between 2000 and 2012. There are only four counties that shift upward with downward neighbors and two counties that shift downward with upward neighbors. The county has a higher probability of moving downward if it has a steady neighbor. Therefore, this spatial pattern also contributes to a strengthening spatial agglomeration of rich and poor counties and intensified regional economic polarization.

The tendency toward the geographic concentration of regional development in Guangxi can be seen through the global Moran's I (Fig. 8). The spatial correlation of GDPPC at the county level has been significant in recent years. The resulting global Moran's I shows an N-shape pattern, which increases from 0.007 in 1989 to 0.167 in 1997, and drops to 0.085 in 2007, but rises dramatically again to 0.219 in 2012.

Furthermore, the LISA cluster maps of GDPPC confirm a positive spatial heterogeneity and vary widely for 1989 and 2012[2] (Fig. 9). In 1989, the Low-Low spatial cluster is in Baise, Hechi and Chongzuo cities, which are all located in WG. This area is becoming a poverty center and has a vulnerable ecological environment. Four rich spatial clusters exist around the Nanning municipal district, located in the BGEZ. The spatial agglomeration with rapid economic growth is enforcing inter-county inequality, as well as inter-municipality inequality. This geographic pattern is closely related to the ecological environment, the presence of ethnic minorities and preferential policies.

Comparing the two years (Fig. 9), the most salient spatial pattern occurs in BGEZ, which is an emerging rich spatial cluster due to policy advantages and a favorable

[2] The Moran scatter plot was developed to assess local instability in spatial association. The four quadrants in the scatter plot correspond to different types of spatial correlation. Spatial outliers are in the upper right (high-high, HH) and lower left (low-low, LL) quadrants, and spatial clusters are in the lower right (high-low, HL) and upper left (low-high, LH) quadrants. HH denotes high values surrounded by high values and LL indicates low values surrounded by low values, etc.

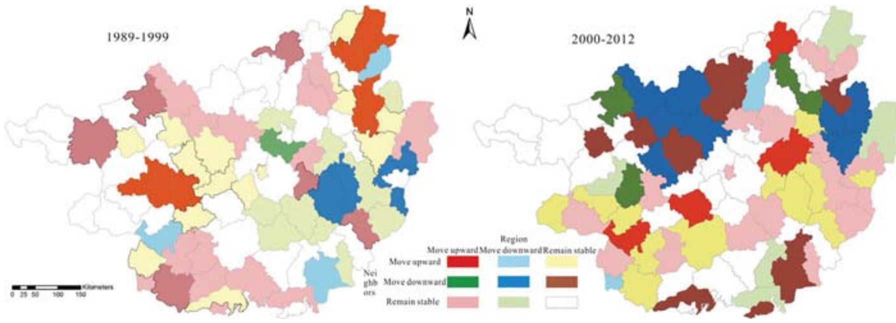

Fig. 7 Global Moran's I of county level GDP per capita in Guangxi, 1989–2012

location. Meanwhile, the WG is becoming a poverty center, a status that remains relatively stable because of its many poverty-stricken and ethnic minority counties accompanied by its WG's fragile ecological environment. This exacerbates inter-county regional inequality but reduces interregional inequality, which is consistent with the computed result of the Theil index (Fig. 2).

Understanding the Mechanisms from a Spatial and Nonlinear Perspective

The underlying mechanisms of the uneven regional development are examined in four regression models with and without nonlinear effects and spatial heterogeneity using 1995 and 2010 datasets (we have no data on rocky desertification or FDI in 1995 and exclude these two variables in the model). We begin the econometric analysis by estimating the baseline linear model using OLS and SLM to address spatial effects (as the robust Lagrange Multiplier tests suggest, the spatial lag model is more appropriate). The two models do not account for nonlinear effects and spatial heterogeneity. Therefore, we also use GWR to tackle non-stationary data by allowing regression model parameters to change over space (Fotheringham et al. 2001). Table 3 reports the summary statistics of variables and the results of regression models, including global (OLS and SLM) and local regressions (GWR), are reported in Tables 4 and 5 and Fig.

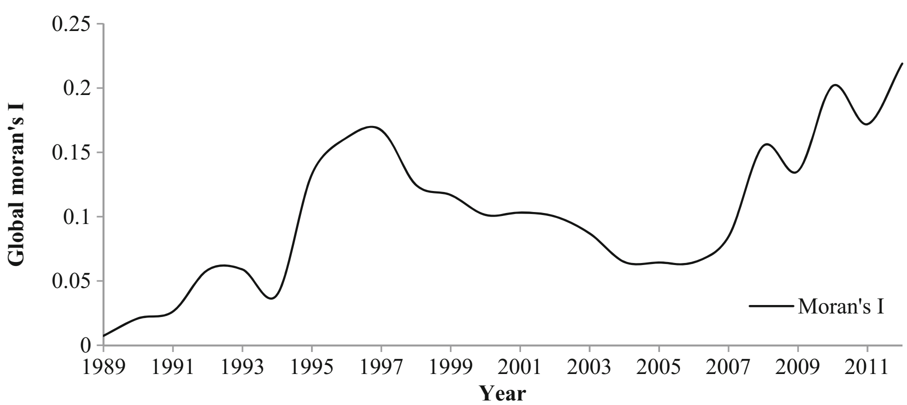

Fig. 8 The LISA cluster map for per capita GDP at the county level in Guangxi, 1989, 2012

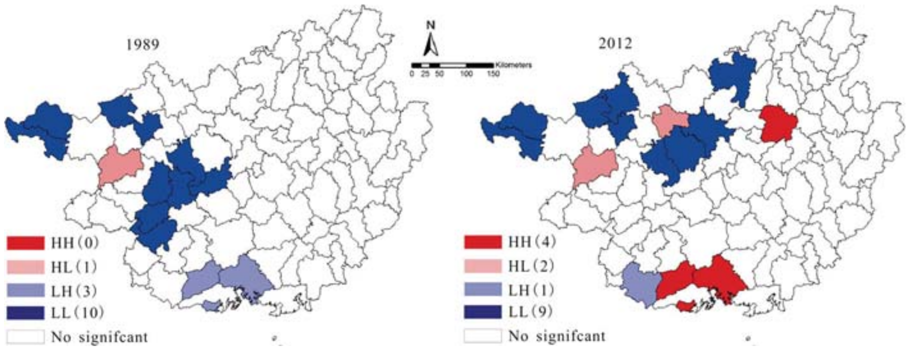

Fig. 9 GWR results for significant explanatory variables

10, while the results of the semiparametric geoadditive models for parametric terms and non-parametric terms that consider spatial dependence, spatial unobserved heterogeneity and nonlinearities are reported in Tables 7 and 8.

The goodness-of-fit statistics, such as the AICs and log-likelihoods, indicate that the data are better fit using spatial analysis techniques. For instance, in 1995, the AIC for the OLS model is 27.69, while for SLM it is 23.88; for the GWR model, the AIC further decreases to −47.80 (Table 6). Similar results are observed from analyses using 2010 data. This clearly points to the fact that model effectiveness could be reduced without considering the potential spatial effects in regression analyses. In addition, the semiparametric geoadditive models show better explanatory power than the parametric models. The PS-SLX models reflect 87% (Adjusted R-square = 0.87) and 93% (Adjusted R-square = 0.93) of GDPPC variations in 1995 and 2010, higher than both OLS models (adjusted R-squares: 0.73; 0.85) and SLM models (adjusted R-squares: 0.78; 0.88), and are close to the GWR models (Adjusted R-squares: 0.89; 0.94). This also demonstrates the better fit and accuracy of the local models and semiparametric geoadditive models. Apparently, Guangxi's economic inequality is sensitive to spatial autocorrelation and clustering.

Evidence from the Linear Models

First, the key explanatory variables with which we are mainly concerned, geography, the environment, ethnicity and spatiality, are closely related to regional development in Guangxi. Moreover, socioeconomic factors are also linked to per capita GDP. The high level of significance for the variables confirms that such determinants are relevant in explaining the mechanisms of regional inequality at the county level in Guangxi and that a multi-mechanism framework is appropriate. SLOPE and DES, which were chosen as two proxies for the effect of geography and environment, exhibit negative relationships with per capita GDP in 2010 (Tables 4 and 5). The regression coefficients are −0.5774 and −4.1109 at the 0.01 significant levels respectively in OLS model and −0.4575 and −3.7333 at the 0.01 significant levels respectively in SLM. Varying relationships in the local analysis show that geography and environment have a larger effect in WG because of the complicated terrain and fragile ecological environment (Fig. 10). The implication of the model is that the economic development of counties is

Table 3 Summary statistics of dependent and predictor variables

Variables	Unit	1995				2010			
		Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
GDPPC	Yuan	3457.267	2068.957	1021.177	13522.19	3255.49	1769.184	899.576	11802.51
SLOPE	%	0.685	0.211	0.012	0.970	0.513	0.223	0.002	0.891
ELE	Km	1158.022	404.216	115.000	1994	1158.022	404.216	115	1994
DES	%					0.010	0.015	0	0.104
PMP	%	0.493	0.364	0.002	0.998	0.499	0.364	0.002	0.987
EMAC		0.135	0.344	0.000	1	0.135	0.343	0	1
EDZ		0.214	0.412	0.000	1	0.214	0.412	0	1
DISTANCE	Km	151.140	73.750	0.000	385.043	151.140	73.750	0.000	385.043
IND	%	0.293	0.116	0.110	0.681	0.418	0.106	0.207	0.728
FIXPC	Yuan	680.112	1134.587	96.636	8968.321	11158.04	7876.717	1929.941	42804.63
FDIPC	Yuan					2145.182	6038.323	0	44874.08
DEC	%	0.784	0.779	0.288	6.739	0.757	0.370	0.298	2.326
ROADDEN	Km/km^2	0.208	0.095	0.067	0.494	0.480	0.169	0.178	0.936
POPDEN	$Persons/km^2$	0.022	0.020	0.004	0.126	0.025	0.021	0.005	0.134

Table 4 Global OLS regression results

Dependent variable	GDPPC 2010				GDPPC 1995			
Parameter	Estimate	Std Err	T-value	*P*-value	Estimate	Std Err	T-value	*P*-value
cons	3.6359	0.6331	5.74	0.000	5.7732	0.8125	7.105	0.000
SLOPE	−0.5774	0.1756	−3.289	0.002	−0.0431	0.1972	−0.219	0.828
LNELE	0.0460	0.0690	0.667	0.507	0.1375	0.1087	1.265	0.210
DES	−4.1109	1.5075	−2.727	0.008				
PMP	−0.0138	0.0788	−0.175	0.862	−0.3967	0.1056	−3.755	0.000
EMAC	−0.0188	0.0684	−0.275	0.784	−0.1402	0.0936	−1.500	0.138
EDZ	−0.0171	0.0698	−0.245	0.807	0.0926	0.1006	0.920	0.361
LNDISTANCE	−0.0731	0.0219	−3.332	0.001	−0.0580	0.0299	−1.939	0.056
IND	1.1435	0.2406	4.754	0.000	0.9447	0.3603	2.622	0.011
LNFIXPC	0.4479	0.0595	7.531	0.000	0.2284	0.0613	3.725	0.000
LNFDIPC	0.0054	0.0063	0.866	0.389				
DEC	0.1392	0.0977	1.424	0.159	0.1018	0.0600	1.696	0.094
ROADDEN	0.1067	0.1822	0.586	0.560	0.3009	0.4913	0.612	0.542
POPDEN	−1.4241	1.6082	−0.886	0.379	−0.5423	2.2241	−0.244	0.808

2010: F-statistic: 38.75 on 14 and 75 DF, *p*-value: 6.2e-028; 1995: F-statistic: 23.08 on 12 and 77 DF, *p*-value: 4.7e-020

constrained by their geographic foundations, which also intensify the regional inequality in the province. The significant positive coefficient of WDES shows the same result (Table 7). EMAC is also negatively related to per capita GDP in both years, which suggests that regional development in Guangxi is affected by ethnicity features. The insignificant variable of EDZ implies that policy does not effectively promote local economic development. The significance of the negative LNDISTANCE in both years,

Table 5 Spatial regression results

Variables	2010				1995			
	Coefficient	Std Err	t/z-value	Pr(>|t|)	Coefficient	Std Err	t/z-value	Pr(>|t|)
W-LNGDPPC	0.2628	0.1251	2.101	0.036	0.3648	0.1475	2.474	0.013
SLOPE	−0.4575	0.1651	−2.771	0.006	0.0863	0.1915	0.451	0.652
LNELE	0.0176	0.0623	0.282	0.778	0.1429	0.0977	1.464	0.143
DES	−3.7333	1.3576	−2.750	0.006				
PMP	0.0251	0.0715	0.350	0.726	−0.2401	0.1058	−2.269	0.023
EMAC	−0.0279	0.0609	−0.458	0.647	−0.1935	0.0864	−2.238	0.025
EDZ	−0.0084	0.0622	−0.134	0.893	0.1018	0.0901	1.130	0.259
LNDISTANCE	−0.0702	0.0195	−3.597	0.000	−0.0527	0.0268	−1.963	0.050
IND	1.2239	0.2162	5.660	0.000	1.1202	0.3272	3.424	0.001
LNFIXPC	0.4466	0.0530	8.429	0.000	0.2032	0.0554	3.666	0.000
LNFDIPC	0.0041	0.0056	0.736	0.462				
DEC	0.0927	0.0905	1.024	0.306	0.1175	0.0541	2.172	0.030
ROADDEN	0.1497	0.1625	0.921	0.357	0.3933	0.4420	0.890	0.374
POPDEN	−0.5870	1.4931	−0.393	0.694	−0.2354	2.0064	−0.117	0.907
cons	1.6198	1.1392	1.422	0.155	2.6969	1.4930	1.806	0.071

Rho: 0.2628 LR test value: 5.0886 *p*-value: 0.024, Log likelihood: 33.9788 for lag model, Robust Lagrange multiplier test: 4.564, on 1 DF, *p*-value = 0.033; Rho: 0.3648 LR test value: 5.8044 *p*-value: 0.016, Log likelihood: 1.0582 for lag model, Robust Lagrange multiplier test: 4.548, on 1 DF, *p*-value = 0.033

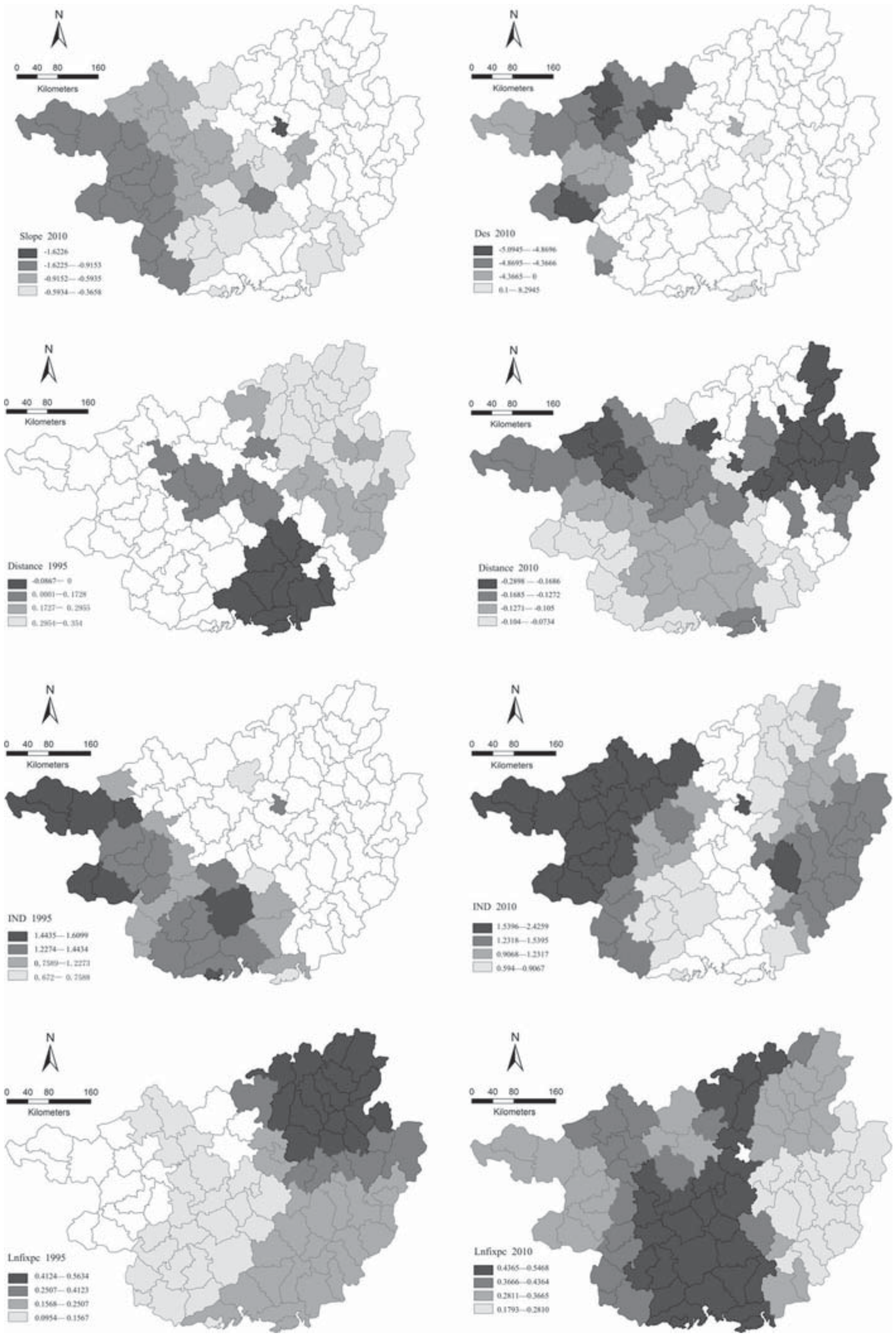

Fig. 10 Smooth effect of significant explanatory variables

as illustrated by the coefficients of −0.0731 and −0.058 for 2010 and 1995 respectively in OLS model, and −0.0702 and −0.0527 for 2010 and 1995 respectively in SLM,

Table 6 Test for the models

Models	2010				1995			
	OLS	SLM	GWR	PS-SLX	OLS	SLM	GWR	PS-SLX
Adjusted R^2	0.848	0.88	0.94	0.93	0.734	0.78	0.89	0.87
AIC	−34.87	−37.96	−116.66		27.69	23.88	−47.80	

indicates that regional development in Guangxi is positively associated with the county's location (core position is preferred). Distance exerts influence in the counties east of Nanning (the capital of the province) in 1995, while the core-periphery structure with the center of Liuzhou and Nanning can be clearly seen through the effect of distance in 2010 (Fig. 10). This also reflects that the counties close to the core region (capital and industrial center) tend to outgrow other counties. This singles out the importance of location naturally in the uneven regional development in Guangxi.

Second, the FIX and IND variables are statistically significant in both 1995 and 2010 in the global analysis and have an increasing positive coefficient, the former coefficients are 0.2284 and 0.4479 for OLS model and 0.2032 and 0.4466 for SLM while the latter coefficients are 0.9447 and 1.1435 for OLS model and 1.1202 and 1.2239 for SLM. This finding implies that regional development in Guangxi still largely relies on investment and industrialization. The GWR model indicates that investment is positively associated with economic levels in Guilin and its surroundings in 1995. However, the BGEZ and Liuzhou have larger investment effects in 2010, which greatly promote neighboring areas and form a huge positive cluster covering the whole province, especially the central province (Fig. 10). The influence of industrialization (IND) expresses more complex spatial variations. Secondary industry development has a stronger impact on Nanning municipal district, Liuzhou municipal district and the neighboring BGEZ, as rich regions, and on Baise as a poverty city in 1995, while only backward areas, including Baise, Hechi, and Liuzhou (industrial center city) were influenced by industrialization in 2010 (Fig. 10). Globalization is not significant in 2010, which illustrates that the influence of globalization is limited by the small-scale FDI in Guangxi. The DEC variable tells the same story. In addition, the infrastructure indicator, ROADDEN, and the market potential indicator, POPDEN, are statistically insignificant and do not effectively become components of economic acceleration.

Evidence from the Semiparametric Models

In Tables 7 and 8, we report the estimation results of the semiparametric model in smooth univariate terms to identify the possible nonlinear effects of the explanatory variables and the smooth interaction between latitude and longitude to account for unobserved spatial heterogeneity. We use a smoothing parameter related to the penalty function to balance between bias and variance of the estimates (Basile et al. 2013). The F-tests for the overall significance of the smooth terms and their effective degrees of freedom (edf) are also reported, and these suggest the significance of some univariate smooth terms in the model. All of the edf reveal nonlinearity, as they are greater than one (if the edf is equal to one, a linear relationship cannot be rejected).

Table 7 Semiparametric geoadditive model for parametric terms

Variables	2010				1995			
	Estimate	Std. Err	t value	Pr(>|t|)	Estimate	Std. Err	t value	Pr(>|t|)
(Intercept)	12.44	2.567	4.844	0.000 ***	−2.9573	11.6057	−0.255	0.8
SLOPE	−0.3698	0.2154	−1.717	0.093 *				
WSLOPE	2.245	2.973	0.755	0.454				
LNELE					0.0077	0.1032	0.075	0.940
WLNELE					1.5894	1.5238	1.043	0.301
DES	−1.423	1.692	−0.841	0.405				
WDES	45.87	25.37	1.808	0.077*				
PMP					−0.1141	0.1639	−0.696	0.489
WPMP					−1.4630	1.1381	−1.285	0.204
EMAC	−0.1821	0.0732	−2.487	0.017 **	−0.2434	0.0929	−2.621	0.011**
WEMAC	−1.845	0.9989	−1.847	0.071*	−2.7254	1.3946	−1.954	0.056 *
EDZ	0.1152	0.0755	1.525	0.134	0.0811	0.0868	0.935	0.354
WEDZ	2.585	1.362	1.898	0.064*	−1.7737	1.5385	−1.153	0.254
LNDISTANCE	−0.0779	0.0272	−2.865	0.006 ***	−0.0801	0.0268	−2.991	0.004 ***
WLNDISTANCE	−1.615	0.4848	−3.332	0.002 ***	−0.7107	0.5779	−1.230	0.224
IND	1.278	0.2146	5.954	0.000 ***	1.5930	0.3348	4.758	0.000 ***
WIND	−1.347	1.851	−0.727	0.471	3.8862	2.1801	1.783	0.080 *
LNFIXPC	0.3113	0.0584	5.335	0.000 ***	0.1465	0.0501	2.927	0.005***
WLNFIXPC	−1.347	1.851	−0.727	0.471	3.8862	2.1801	1.783	0.080 *
LNFDIPC	−0.0006	0.0062	−0.091	0.928				
WLNFDIPC	0.0472	0.1118	0.422	0.675				
DEC					0.2649	0.0705	3.759	0.000 ***
WDEC					2.6914	0.7228	3.723	0.000 ***
ROADDEN					0.3744	0.409	0.916	0.364
WROADDEN					−3.8823	6.4894	−0.598	0.552
POPDEN	−3.889	1.652	−2.354	0.023 **				
WPOPDEN	−14.96	29.27	−0.511	0.612				

2010: R-sq.(adj) = 0.93, Explained deviance = 96.3%, GCV score = 0.0305, Scale est. = 0.0159, n = 89; 1995: R-sq.(adj) = 0.87, Explained deviance = 91.5%, GCV score = 0.0558, Scale est. = 0.0354, n = 89. Signif. codes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The smoothed partial effects of the univariate terms are portrayed, and the shaded areas highlight the 95% credibility intervals. The LNELE plot (Fig. 11a) confirms that the effect of altitude appears to be nonlinear, and an inverted U-shaped relationship is displayed between altitude and per capita GDP in 2010: ceteris paribus, a higher altitude increases local per capita GDP and the positive effect of altitude fades as the altitude reaches some threshold value. We also find a hump-shaped relationship between slope, SLOPE, and local economic development in 1995 (Fig. 11b: the positive effect of overall slope remains steady and fades as the slope reaches a threshold value, after which infrastructure costs rise. PMP has a negative effect in 1995 in the linear models, while a corresponding smooth interaction term (WPMP), the proportion of minority population neighboring regions, demonstrates a nonlinear relationship in 2010 (Fig. 11c): the negative effect of adjacent ethnic areas declines gradually, as it is null up to a certain threshold, after which it becomes negative and has a positive effect.

Although there is no significant linear relationship between ROADDEN and per capita GDP, the plots of smooth terms show varying effects on regional development, and a V-shaped relationship emerges in 2010 (Fig. 11d): starting from low levels of

Table 8 Semiparametric geoadditive model for non-parametric terms

Variables	2010				1995			
	edf	Ref.df	F	*p*-value	edf	Ref.df	F	*p*-value
s(Wslope)					5.131	6.226	2.384	0.042 **
s(slope)					2.946	3.563	3.297	0.025 **
s(lnele)	2.086	2.472	3.682	0.022 **				
s(Wlnele)	7.169	8.053	2.856	0.01 ***				
s(pmp)	1.870	2.299	1.708	0.246				
s(Wpmp)	2.594	3.279	2.709	0.051*				
s(dec)	2.257	2.812	2.231	0.135				
s(Wdec)	2.308	2.915	0.553	0.577				
s(roadden)	3.074	3.660	8.009	0.000***				
s(Wroadden)	3.311	4.087	1.863	0.123				
s(popden)					1.299	1.524	2.283	0.113
s(Wpopden)					5.271	6.398	2.527	0.026**

2010: R-sq.(adj) = 0.93, Explained deviance = 96.3%, GCV score = 0.0305, Scale est. = 0.0159, n = 89; 1995: R-sq.(adj) = 0.87, Explained deviance = 91.5%, GCV score = 0.0558, Scale est. = 0.0354, n = 89. Signif. codes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ROADDEN, an increase in road density has a negative effect on development; after a certain threshold, however, an increase in road density has a positive effect on development. WPOPDEN, population density neighboring areas, and per capita GDP display a wave-shaped relationship in 1995 (Fig. 11e).

To summarize, the regression results demonstrate that the impact of geography, environment, ethnicity, policy and location on regional inequality is significant. Moreover, regional development is influenced by socioeconomic factors such as investment and industrialization for Guangxi. The results also show that globalization and decentralization play a minor role in regional development. Compared to these

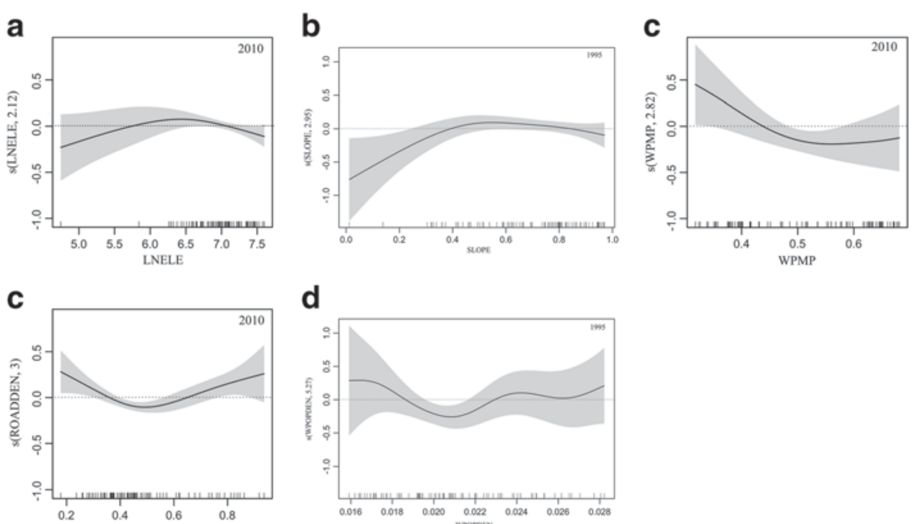

Fig. 11 Smooth effect of significant explanatory variables

factors in the linear models, other geographic and environmental factors, such as altitude and slope, ethnic composition (the proportion of minority population), and socioeconomic conditions, such as infrastructure (road density) and market potential (population density), have a significant nonlinear relationship with local economic development. However, the linear models (Table 5) mask these nonlinearities and bring us to conclude that these variables have no significant effect.

Conclusions

Studies on intra-provincial inequality and development in poorer regions remain limited, and more efforts are needed to better the understanding of the patterns and mechanisms underlying regional inequality. In this paper, we analyze the multiscalar patterns and spatial-temporal dynamics of regional inequality for Guangxi over the past two decades. We use both linear models and semiparametric models (consider spatial dependence, spatial unobserved heterogeneity and nonlinearities) to investigate the effect on regional inequality of various factors characterizing geography, environment, ethnicity, spatiality and the socio-economy. This paper has confirmed the applicability of a multi-scale and multi-mechanism framework for intra-provincial inequality in poorer areas. A similar upward trend of inequalities at county and municipality scales has been revealed, and it is sensitive to geographic scales. Interregional inequality stays consistently steady with a slight increase in recent years. The contribution of this inequality within the BGEZ, XREB and WG has been a main source of uneven regional development, which differs from the findings for developed provinces, such as Zhejiang (Yue et al. 2014) and Guangdong (Liao and Wei 2012). Moreover, we have demonstrated the increasing polarization of regional development and the significance of spatial dependence and self-reinforcing agglomeration in recent years. BGEZ is emerging as a rich spatial cluster, and WG is becoming a poverty center.

The results of the multi-mechanism framework provide solid evidence that geography, environment and ethnicity are significant driving forces causing regional inequality in Guangxi. They confirm that geographic environment is the basis for the structural characteristics of the poor western provinces and that severe geographic constraints on development are hard to completely overcome. These results have also affirmed other scholars' viewpoints (Naughton 2004; Wei and Fang 2006). The GWR model proves that significant heterogeneous spatial structure exists in Guangxi. The flexibility of the semiparametric approach has allowed us to appreciate that some local characteristics have a nonlinear effect on economic development. The positive effect of geography (captured by slope and altitude) appears to fade as the topography reaches some threshold value, thus emerging as a hump-shaped relationship between slope and local economic development, as well as between altitude and regional development. The environment is also an important factor used to understand regional inequality and has a larger effect in poorer WG. This is because rocky land desertification often indirectly leads to a lack of transportation and communication in remote areas, worsens living conditions, increases the illiteracy rate, and even deteriorates the economic, social and cultural life of residents (Wang et al. 2004; Jiang et al. 2011; Jiang et al. 2014). The conclusion regarding the dominant role played by the spatial distribution of minorities in the explanation of economic disparity is consistent with other research findings (Cao 2010). A higher proportion of a minority population in a neighboring region has a negative effect on regional development and a positive effect at a certain threshold. Spatiality and location are indispensable influential factors and will play a more important role in regional inequality because the core-periphery structure tends to be maintained and intensified as the BGEZ economy further develops.

Both government investment and industrialization continue to be the traditional influential factors. Meanwhile, the impact of globalization and decentralization is not obvious, and policy is not clear regarding regional inequality for Guangxi. Infrastructure and market potential have a nonlinear relationship with regional inequality. This finding is unlike the conclusions drawn for developed provinces, such as Zhejiang (Wei and Ye 2009), Guangdong (Liao and Wei 2012) and Jiangsu (Wei et al. 2011), in which a higher infrastructure (computed by road density) has a negative impact on development and then an increasingly positive effect after a certain threshold. The results also verify that the analysis framework from previous research is not applicable to less-developed regions and that the value of the geography framework is asserted. Guangxi's empirical analysis demonstrates that regional inequality must be understood by taking into account the analysis and synthesis of the effects of geography, environment, ethnicity and spatiality. We believe this analysis framework is necessary to better understand the mechanisms of regional inequality in poorer Western China.

The mechanisms underlying regional inequality are complicated, and they are distinct for different regions and different development stages in China. We argue that this research effort helps enrich our understanding of the spatial and temporal complexity of provincial inequality patterns and the mechanisms affecting backward regions in China. Although the results show that industrialization and investment have exerted influence in the uneven regional development, the huge impacts of geography, environment and ethnic composition on regional inequality also have been confirmed. Therefore, it is necessary to account for local agents and the interaction of global forces and localities while investigating the mechanisms causing regional inequality in China (Wei 2015).

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