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Does misallocation of land resources reduce urban green total factor productivity? An analysis of city-level panel data in China

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ABSTRACT

Although the "developing by land" model substantially stimulates industrialization and urbanization, the land-resource-allocation model with "high-cost and low-efficiency" that makes up most of the industry can potentially enlarge resource consumption and intensify environmental pollution. This paper examines the mechanisms of the impacts of land resource misallocation on urban green total factor productivity (GTFP), using a dataset of China's 277 cities at the prefecture (and higher) level from 2006 to 2013. Fundamental and spatial econometric models are estimated to empirically investigate the effects of land resource misallocation on GTFP and explore the spillover effects as well as regional differences. The results reveal that the misallocation of land resources directly reduces the GTFP of the city and hinders the development of GTFP in neighboring cities. The mismatch of land allocation is a major reason for restricting the improvement of the overall productivity that accounts for energy consumption and environmental degradation, with mechanisms involving the undermined technological innovation and industrial structure upgrading. Regional heterogeneity analysis suggests that the unfavorable effects of land resource misallocation on GTFP are indirect and associated with spillover effects for sample cities in eastern and central regions. The mechanisms involving innovation capacity and manufacturing agglomeration also exhibit substantial regional disparities among eastern, western, and central regions. By optimizing the allocation of land resources, enterprises with strong innovation capabilities and belonging to modern service industries can obtain more land use, enhancing their motivation for technological innovation and optimizing industrial structure and achieving high-quality economic growth and sustainable development.

1. Introduction

The desirable socioeconomic development is often accompanied and undermined by undesirable environmental costs. With simultaneously dramatic economic growth and serious greenhouse gas emissions, China has been facing challenges along the way towards an environmentally sustainable future (Zhang, 2000; Liu et al., 2012; Zhang et al., 2013; Qi et al., 2016; Elzen et al., 2016). Since the opening reform in 1978, China's economy has experienced a double-digit growth in economy (Zhang et al., 2018), but such leapfrog brings threats to the natural environment at the national scale (Jiang, 2015). For example, the whole country's CO_2 emission in 2012 contributed to 26.7% of the total global emission (Li and Lin, 2015), while in 2016 the nationwide industrial SO_2 production was more than 51 million tons (China Statistic Year Book). To tackle the adverse economic-environmental relationship, the Chinese government has implemented several stringent environmental regulations, carrying ambitious goals of mitigating SO_2 and NO_x emissions by 3% in 2018.[1] These policy practices attempt to integrate the "green development" into the total factor productivity (TFP) (Jiang, 2015; Rusiawan et al., 2015) to harmonize output growth and environmental conservation. To achieve the goal of sustainable development, it is necessary to evaluate the overall productivity while considering undesirable outputs, also known as green total factor productivity (GTFP) (Repetto et al., 1997; Xepapadeas et al., 2007; Zhao et al., 2015).

Land resource allocation is a critical component of socioeconomic development in China as well as in other countries worldwide (Ding and Lichtenberg, 2011; Hyde, 2013; Verburg et al., 2013; Nasikh et al., 2021). The ideally rational allocation of land resources over time and

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[1] Website: www.gov.cn/xinwen/2018–03/22/content_5276608.htm/

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space based on regional socio-economic statuses is the main measure for optimal land planning and utilization. However, the distribution of land resources often faces challenges, among which the mismatch or misallocation of land resources (land resource misallocation, LRM) is one of the most fundamental issues in land use planning (Li et al., 2016; Li, 2021). The biased allocation of urban construction land makes the industrial land exhibit a reverse mismatch trend that the return is higher than the actual land price (Li et al., 2016). The land strategy pursued by local governments for maximizing fiscal taxation and political promotion is more biased in industrial and mining warehousing, often resulting in mismatches in land use structure (Huang and Du, 2017; Han et al., 2020). The "developing by land" strategy has greatly reduced the cost of industrial enterprises, squeezed the resources of emerging enterprises, and strengthened the structural rigidity of low-end industries, which all together formed an extensive economic development model. Despite the temporarily strong impetus for industrialization and urbanization, this "high-cost, low-efficiency" mode of land resource allocation in a longer run would enlarge serious resource consumption, exacerbate environmental pollution, and subsequently hamper TFP that considers unfavorable outputs. This study explores the relationships between LRM and GTFP at the city level, aiming to address the urgent needs for sustainable development through the lens of urban land use and planning and land resource distribution.

2. Literature review

Green total factor productivity (GTFP) is an essential economic indicator that takes environmental pollution and energy consumption into account (Zhao et al., 2015), which is more in agreement with the notion of green economic development in the new era. As for the research on GTFP, several scholars mainly focused on the driving factors that influence the growth or dynamic of GTFP. This paper discusses the mechanisms of improving (or changing) GTFP by concerning the promoting effect, inhibiting effect, and heterogeneity analysis. Scholars of "promotion theory" believe that foreign direct investment (FDI) (Yu et al., 2021), government intervention (Lin and Chen, 2018), international trade behavior (Cao and Wang, 2017) and financial agglomeration effect (Xie et al., 2021) are all key factors to improve GTFP. Some scholars have also analyzed productivity from the perspective of policy governance. They found that the implementation of urban environmental legislation or carbon trading policies will produce an "innovative compensation" effect, which can urge enterprises to adopt advanced technology and management, thereby improving GTFP (Rubashkina et al., 2015; Li et al., 2022; Zhang et al., 2022). However, scholars of "inhibition theory" have discovered that land transfer has no significant effect on industrial GTFP (e.g., Yang et al., 2022). Moreover, the level of human capital, technological innovation and environmental regulation will produce a threshold effect or factor substitution effect, which can hinder the process of growing GTFP (Yang et al., 2017; Li et al., 2021). Finally, other scholars have conducted specialized studies on heterogeneity analysis (Xie et al., 2019; Zhang et al., 2022). Xu (2022) found that the difference in the level of GTFP in the eastern, central and western regions was mainly caused by endogenous technological progress. Lu et al. (2020) found that the rationalization of industrial structure significantly enhances the development of GTFP, and its influence shows a decreasing trend from the west to the middle and the east. Their study is based on panel data at the level of 30 provincial administrative regions in China from 2004 to 2016, which lacks city-level heterogeneity-based exploration. In this study, we use urban data of 277 prefecture-level cities for regional heterogeneity analysis of land resource allocation on GTFP. In addition, the research perspective and the explanatory variables are measured differently. Lu et al. (2020) measured land transfer marketization indicators by price weighting method and explored the impact of the interaction between land transfer marketization and industrial structure rationalization on GTFP from the perspective of land transfer marketization. Here, we provide a distinct perspective by exploring the impact of land resource mismatch in reducing GTFP by inhibiting technological innovation and industrial structure upgrading, and we measure the land resource mismatch indicator based on a transcendental log production function form with real prices.

In the existing literature, studies worldwide mostly focused on examining TFP under activities of land resource allocation, but little on GTFP has been emphasized. The difference in TFP between underdeveloped and developed countries is largely due to the more serious problem of resource misallocation in underdeveloped countries comparing to their counterparts (Alfaro et al., 2009; Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009). Some studies using economic models showed that the misallocation of land resources has an inverted U-shape relationship with TFP (e.g., Vollrath, 2009), while others suggested a negative effect of land resource mismatch on TFP (e.g., Restuccia and Rogerson, 2013). Based on the survey data of regional households and the two-sector general equilibrium model, respectively, Restuccia and Santaeulalia-Llopis (2017) and Chen (2017) both found that the mismatch of agricultural land use would seriously reduce agricultural productivity. Gottlieb and Grobovšek (2019) reported that, in Ethiopia, restoring transferability of in public land-use rights would increase gross domestic product (GDP) by 9% and agricultural productivity by more. Le (2020) used a quantitative model and micro-level data to study land use right and total productivity in Vietnam and found that per capita GDP would increase by 8.03% were all land use restrictions cancelled. Meanwhile, land transfer behavior with reasonable low-price is shown to be conducive to promoting TFP in some cases (Chen et al., 2017; Ding et al., 2021). In other cases, a higher percentage of construction land for a city's agreement tends to hamper the productivity due to the lower efficiency of resource allocation among industrial enterprises (Li et al., 2016; Zhang and Yu, 2019; Li, 2021). Alternatively, several studies focused primarily on the impacts of land finance and land transfer marketization on GTFP (Jiang et al., 2019; Xie et al., 2019; Chen et al., 2020). For example, Xie et al. (2019) investigated China's 283 cities and showed that land finance could improve GTFP in a city and its surrounding areas.

Although many studies have examined on LRM and TFP, less is known on how the misallocation of land resources influences GTFP that considers non-market outputs. It is also urged to systematically consider time and space factors when evaluating the spatial spillover effects of land resource mismatch on GTFP, as well as extending such effects for spatial heterogeneity analysis. This paper fills this gap by investigating the influence of misallocation of land resources on GTFP with spatial spillover effects and exploring three possible pathways including innovation capacity, industrial structure, and manufacturing agglomeration.

3. Conceptual framework and hypotheses

We propose a conceptual framework (Fig. 1) to guide the analysis of direct and indirect associations between land resource misallocation (LRM) and green total factor productivity (GTFP) in urban China, as well as the regional differences and the mediating effects via three key mechanisms, including innovation capacity, industrial structure, and manufacturing agglomeration.

3.1. Direct impact of LRM on GTFP

Driven by China's current performance appraisal system focusing on economic development, local governments aim to maximize investment to promote economy by selling land of industry at relatively low prices and expanding industrial land use (Yang et al., 2014). Such improper government regulation have attracted a large number of low-productivity enterprises to make investment, inevitably crowding out high-productivity enterprises with nevertheless insufficient investments (Shao et al., 2016). Furthermore, local governments are inclined to limit the sale of commercial or residential land by setting much

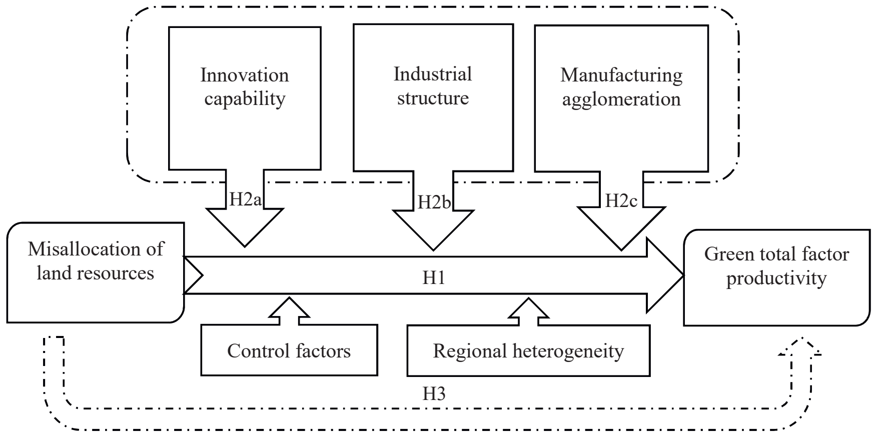

Fig. 1. Conceptual framework for effects of land resource misallocation on green total factor productivity. Solid arrows indicate direct effects and interactions, while dash arrows indicate effects involving spatial spillover effects.

higher prices, known as the “double second-hand” strategy for land supply (Li et al., 2016; Gao et al., 2021). This strategy has resulted in unbalanced development with high weights for the secondary industry but low for the tertiary industry (Li and Luo, 2017). Thus, the first hypothesis, Hypothesis 1 (H1), is formulated as:

H1. The misallocation of land resources directly reduces the enterprises’ GTFP by engaging more low-productivity enterprises with high pollutions and emissions in the land market given the relatively low price of allocated land.

3.2. Impacts of mediating factors of LRM on GTFP

Innovation Capacity. Given sufficient supply of factors, producers with higher production efficiency will continue to scale up until reaching equal marginal benefits and marginal costs (Alfaro et al., 2009; Adamopoulos and Restuccia, 2014). When the land market is balanced, the marginal output of land should equal to the marginal cost of land; the land sold at a low price can lead to a decrease in the marginal output of the enterprise, potentially reducing corporate innovation (Hsieh and Klenow, 2009). The selling of land to enterprises at extremely low prices or even “zero land prices” can substantially reduce revenues for local governments. Accordingly, local governments would strengthen tax collection and management to increase tax revenue, leading to reduction of enterprises’ investments in research and development and subsequently inhibiting the transformation towards the knowledge-intensive model. This process would eventually hinder the improvement of urban GTFP.

Industrial Structure. Since the opening-up reform in 1978, the focus of the assessment system of Chinese cadres have shifted from political loyalty to economic performance during the tenure of officials (Li and Zhou, 2005). During the process of competing for industrial land transfer, local governments have intentionally biased heavy industries (e.g., manufacture, construction and real estate) that can boost GDP and fiscal revenues, resulting in excessive and accelerated paces of industrialization (Restuccia and Rogerson, 2013). This bias has greatly modified the industrial structure, of which heavy industries make up the greatest share while the tertiary industry with modern services trivial. The domination of high-emission and high-pollution industries can further strengthen the rigidity of low-efficiency for the whole structure (Cao, 2008).

Manufacturing Agglomeration. With the large investment from low-productivity enterprises, the low land use efficiency can hinder the transformation of industrial structure from labor-concentrated industry to capital- and technology-focused industry that is not conducive to high-end manufacturing agglomeration (Li and Luo, 2017). This land transfer behavior has been intervened by intrinsic impulse of local governments (Shao et al., 2016). Such powerful intervention can not only catalyze unsustainable economic development but also inhibit the evolution of industrial clusters of high-end industries, weakening the economic effects of industrial agglomeration.

Based on the above literature review, the following hypotheses, Hypotheses 2a, 2b and 2c (H2a, H2b and H2c), can be formulated.

H2a. The misallocation of land resources inhibits the innovation capacity of the city, which negatively affects the growth of GTFP.

H2b. The mismatch in land resources supports heavy industry enterprises in a biased manner and reduces the production allocation with raised costs of modern service industry, which in turn undermines urban GTFP.

H2c. Since land transfer behavior belongs to government intervention rather than market regulation, many low-end manufacturing enterprises with low production efficiency have entered the jurisdiction, formed a mode of extensive economic development, and weakened the benign effect of industrial agglomeration on GTFP.

3.3. Spatial spillover effects

The land element not only spatially mediates urban socioeconomic activities and agglomeration, but also firmly safeguards the steady growth of economy (Shao et al., 2016). Given the strong interrelationship between land and capital elements (e.g., labor as human capital), the misallocation of land elements will also lead to the overall mismatch between capital elements across regions (Li et al., 2016). In addition, local governments’ decisions on land transfer have strategic interactions of competitive imitation, which can be considered as the joint reaction of self-adjustment and competitors (Li et al., 2013). For example, land finance in one place can be transmitted to its surrounding areas; the formation of land transfer plans of that region can also depend on the decisions made by its “neighbors”. Hence, both land resources themselves and land transfer behavior can have spatial spillover effects. Accordingly, Hypothesis 3 (H3) is as follows.

H3. The misallocation of land resources in one city has effects of spatial spillover on its nearby cities that indirectly influence the city’s GTFP.

4. Data and methods

4.1. Data collection

Considering data availability and reliability, the investigation in the present study drew on data of 277 cities in China during 2006–2013 for the analysis (Fig. 2). Data sources include City Statistical Yearbook, Industrial Enterprise Database, Land and Resources Statistics Yearbook, Ministry of Land and Resources website, Statistical Yearbook, and Urban Construction Statistical Yearbook in China. All data sources refer to the years from 2007 to 2014 to correspond the study period. To consider the effects of inflation, all currency values were deflated based on 2006 prices.

4.2. Description of variables

4.2.1. Outcome variable

GTFP is the outcome variable of interest. GTFP is defined as total factor productivity (TFP) that incorporates resource and environmental factors (Cao, 2008; Li and Lin, 2015), such as energy consumption and environmental pollution. Methods for measuring TFP include Solow's residual method that involve parameter estimations (Solow, 1957) and non-parametric approaches based on Data Envelopment Analysis (DEA), such as the Malmquist index model (Chung et al., 1997; Martinho, 2017) and the Slacks-Based Measure (SBM) model (Schatzer et al., 2019). Compared to the Solow estimation, DEA as a holistic factor analysis model has more objectivity in determining parameter weights and assessing system efficiency (Xie et al., 2019; Liu et al., 2020). Among all the DEA approaches, the output-oriented non-radial SBM model can handle excess investments and insufficient outputs, reflecting the reality more effectively. Thus, we adopted the directional SBM approach and used the MaxDEA software to calculate GTFP by following the procedures described in Xie et al. (2019), Han and Ke (2013), and IPCC reports (Eggleston, 2006). Specifically, for example, consensus output data used the summed value of secondary and tertiary industries for each of the 277 cities, while non-consensual output used carbon emissions and SO_2 emissions.

4.2.2. Key explanatory variable

In this study, LRM is the explanatory variable of key interest. We used the network crawler technology to collect urban land transfer data from the Ministry of Land and Resources of China. LRM is obtained by measuring the marginal output of the land element based on the transcendental logarithmic production function and then dividing the marginal output of the land element by its actual price, referring to the methods by Drucker and Feser (2012) and Bai and Bian (2016). The formula of calculating output is:

$$\ln G_{it} = \gamma_0 + \gamma_1 \ln Q_{it} + \gamma_2 \ln K_{it} + \gamma_3 \ln S_{it} + \frac{1}{2}\gamma_4(\ln Q_{it})^2 + \frac{1}{2}\gamma_5(\ln K_{it})^2 + \frac{1}{2}\gamma_6(\ln S_{it})^2 + \gamma_7 \ln Q_{it} \ln K_{it} + \gamma_8 \ln K_{it} \ln S_{it} + \gamma_9 \ln Q_{it} \ln S_{it} + \varepsilon_{it} \tag{1}$$

where γ_0 is the constant; $\gamma_1 \sim \gamma_9$ are elastic coefficients; ε_{it} is the random disturbance term. Meanwhile, G is the regional industrial output, characterized by GDP in the secondary industry; Q is the number of labor in the industrial sector, represented as the number of employees in the urban secondary industry in the municipal area; K is the capital stock in the urban industrial sector, computed as $K_{i,t} = (1-\eta)K_{i,t-1} + F_t/\Omega_{i,t}$ in the municipal district ($K_{i,t}$ is the domestic capital stock; η is the rate of annual depreciation set at 5%; F_t is the fixed investment in assets; $\Omega_{i,t}$ is the index of price of cumulative capital for each city); S is the urban industrial land area, derived from China Urban Construction Statistical Yearbook. For the partial derivative of S in Eq. (1), the marginal output of industrial land (MP_S) can be obtained as:

$$MP_S = \frac{(\gamma_3 + \gamma_6 \ln S + \gamma_8 \ln K + \gamma_9 \ln Q)G}{S} \tag{2}$$

Finally, the degree of LRM is defined as the ratio of the marginal output of industrial land to its actual price (R):

$$LRM = MP_S/R \tag{3}$$

When LRM equals to 1, there is no misallocation of land resources. When LRM is less than 1, the land use value is less than its actual price and land resources present a positive mismatch; conversely, a LRM value greater than 1 indicates a negative mismatch for land resources.

4.2.3. Covariates

Three additional explanatory variables were considered to confound the effects of LRM on GTFP. These control variables are population, human capital, and urban infrastructure. To estimate their elasticities, we used the natural logarithmic forms for all these control variables for model estimations. The justification and derivation of each control

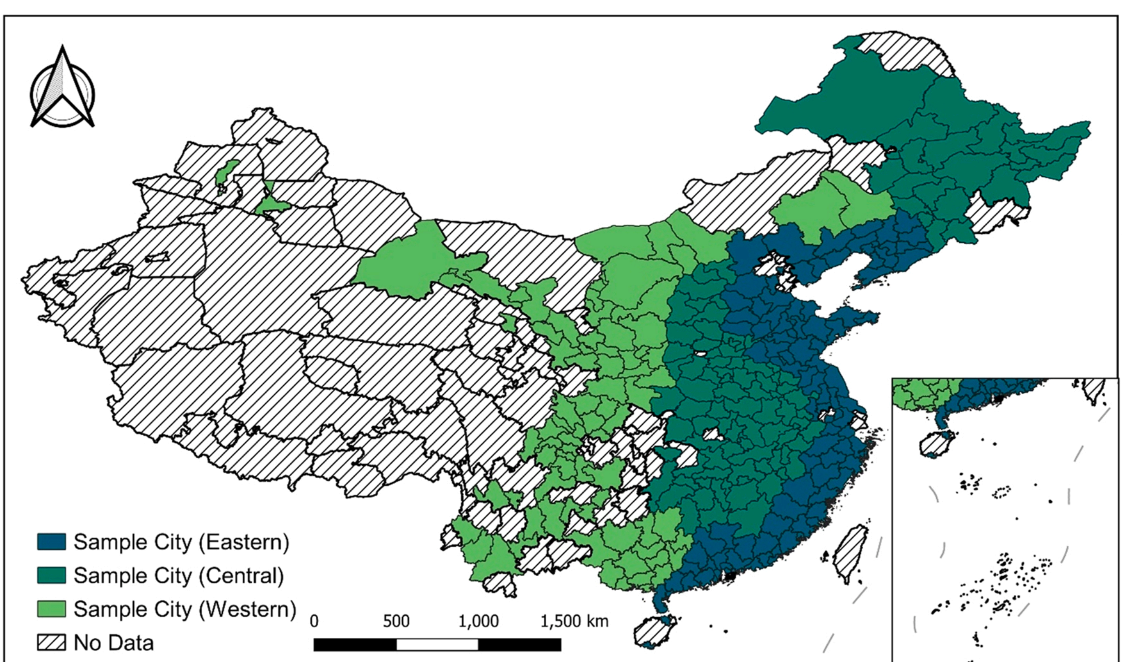

Fig. 2. Map of China with sample cities under investigation.

variable are described as follows.

(1) Population (*P*): Since the realization of urban welfare maximization should be based on the optimal population size of the city (Henderson, 1974), we include the total number of population of each city in the model. (2) Human capital (*EDU*): Human capital such as education can contribute to productivity gains by improving technology absorptive capacity or creating new technologies (Bronzini and Piselli, 2009). Here, human capital is represented as the proportion of students in higher education institutions and ordinary secondary schools in total population. (3) Urban Infrastructure (*PURL*):The growth theory believes that infrastructure improvement can reduce the transportation time and cost of products and services, improve the efficiency of information acquisition, and thus facilitate the diffusion of green technology (Qi and Xu, 2018). Moreover, the economy's own comparative advantage can produce heterogeneity due to different levels of infrastructure (Coşar and Demir, 2016). In this study, we characterize urban infrastructure by using the per capita urban road area of each city.

The descriptive statistics of the outcome variable and explanatory variables in the sample cities in China and different regions are reported in Table S1.

4.3. Spatial autocorrelation

Since the city observations are distributed across regions and associated with spatial attributes, the Moran's I statistic (Moran, 1950) was calculated to test the spatial autocorrelation among GTFP among cities (Zhou et al., 2020). The measurement accuracy of spatial correlation depends largely on the appropriateness of deriving the matrix of spatial weights (*w*). In the existing literature, two most commonly used spatial matrices are the adjacent matrix and the geographic distance matrix (Getis, 2009). Compared to the adjacent matric assignment that is based on adjacent units sharing common boundaries and vertexes, the geographic distance matrix is better at reflecting spatial influence of discrete spatial samples and hence manifesting economic interdependences between urban units in this case. Therefore, to capture spatial attributes and interrelationships of the cities, we construct the geographic distance spatial weight matrix according to cities' Latitude-Longitude positions (Xie et al., 2019) as follows:

$$W_{ij} = 1/{d_{ij}}^2 \tag{4}$$

where ${d_{ij}}^2$ denotes the distance square of two cities at different geographic locations ($i \neq j$); W_{ij} denotes the spatial weight matrix. When i equals to j (W_{ij} is zero), the attenuation parameter is set at 2. All matrices are standardized. According to the calculation, the panel Moran's I value is 0.0525 (statistically significant at 1% significance level), indicating urban GTFP values are spatially and positively correlated, in accordance with the findings in previous studies (Li and Wu, 2017).

4.4. Specification of econometric models

4.4.1. Fundamental econometric model

This paper used panel data to explore the impact of LRM on GTFP. We first adopt the Ordinary Least Square (OLS) panel fixed-effects model (FEM) (Geronimus and Korenman, 1992) to perform the analysis. The specific formula is as follows:

$$GTFP_{it} = a + \theta_1 \ln LRM_{it} + \phi_1 \ln P_{it} + \phi_2 \ln EDU_{it} + \phi_3 \ln PURL_{it} + \alpha_i + \varepsilon_{it} \tag{5}$$

where i and t denote city and year, respectively; *GTFP* represents the comprehensive index value of urban green total factor productivity; *LRM* represents the degree of mismatch in the allocation of land resources. Considering that the main hypothetical idea is that the more serious the land resource mismatch is, the more GTFP decreases. We assume that both positive mismatch and negative mismatch belong to the category of mismatch, so we first perform natural logarithmic transformation on the *LRM*, and then take the absolute value when including it in the model. Thus ln *LRM* denotes the LRM that takes the natural logarithm and then takes the absolute value. θ_1 is the elastic coefficient of LRM, ϕ_1, ϕ_2, ϕ_3 are the elastic coefficients with respective to population size (ln *P*), human capital (ln *EDU*) and urban infrastructure (ln *PURL*). Finally, α_i is a factor that does not change with time but captures differences among individual cities, while ε is the error term with an assumption of the normal distribution. To understand how the LRM effect is confound by other factors, we estimated the model of LRM and GTFP with and without control variables separately, noted as FEM (1) and FEM (2), respectively.

4.4.2. Spatial econometric models

Since the urban GTFP values among cities are spatially correlated, as shown in the Moran's I result (see Section 4.3), the fundamental econometric model that fails to capture the spatial correlation may not provide accurate estimations. In addition, other unobservable variables such as policies at the regional scale leading to spatial interdependence of GTFP among cities are also omitted FEM (1) and FEM (2). Therefore, we further used the spatial econometric model to consider the spatial autocorrelation between LRM and GTFP. The specific spatial measurement model (Han et al., 2018) in a general form can be written as:

$$\begin{aligned} GTFP_{it} &= \delta + \lambda \sum_{j=1, j\neq i}^{N} W_{ij} GTFP_{jt} + \rho X_{it} + \sum_{j=1, j\neq i}^{N} W_{ij} X_{ijt} \theta + \upsilon_i + \sigma_t + \varepsilon_{it} \\ \varepsilon_{it} &= \eta \sum_{j=1, j\neq i}^{N} W_{ij} \varepsilon_{jt} + \phi_{it} \end{aligned} \tag{6}$$

where λ and η are spatial lag and spatial error coefficients, respectively; υ_i and σ_t represent the unobserved spatial and temporal effects, respectively; W_{ij} represents the spatial weight matrix; ε_{it} is the error term; X is a vector of the explanatory variables. Eq. (6) is a general nested model with spatial interaction effects. Empirically, according to whether the values of λ,θandη are 0, the Eq. (6) can be divided into: spatial autoregressive (lag) model (SAR), generalized spatial autoregressive model (SAC), spatially lagged explanatory variable model (SLX), Spatial Durbin Error Model (SDEM), Spatial Error Model (SEM) and Spatial Durbin Model (SDM). Since there may be spatial spillover effect of LRM on GTFP, we follow a set of rigorously statistical tests to determine which form of the spatial economic model is the most appropriate one to perform the analysis (Section 1 in Supplementary Materials). According to the test results (Fig. S1), the space-time fixed-effects Spatial Durbin Model (SDM) is adequate for estimating the econometric model formulated in Eq. (6).

4.4.3. Influencing mechanisms

To further understanding the influence mechanisms of LRM on GTFP, we explore the mediating effects by exploring the LRM effects with three components: the interaction terms of innovation capacity (ln *CXZS*), industrial structure (ln *IS*2), manufacturing agglomeration (ln *EG*) and LRM (ln *LRM*), respectively. This paper used the China Urban Innovation Index measured by Kou and Liu (2017)[2] to indicate urban innovation capacity. The proportion of the gross domestic product (GDP) of the secondary industry in the GDP was used to characterize the industrial structure. We used EG agglomeration index proposed by (Ellison and Glaeser, 1997) as reference to measure the degree of manufacturing agglomeration in China, which is calculated as follows:

[2] Website: bbs.pinggu.org/thread-6769658–1–1.html

$$EG_r = \frac{\sum_r \left(E_r/\sum_r E_r - E_r^h/\sum_r E_r^h\right)^2 - \left[1 - \sum_r \left(E_r/\sum_r E_r\right)^2\right]\sum_i \left(E_h^i/\sum_i E_h^i\right)^2}{\left[1 - \sum_r \left(E_r/\sum_r E_r\right)^2\right]\left[1 - \sum_i \left(E_h^i/\sum_i E_h^i\right)^2\right]} \tag{7}$$

where subscripts r, h and i represent regions, industries, and enterprises, respectively. E_r is the sum of employment in various industries in the region; E_r^h is the number of employed persons in industry h of region r; E_h^i is the number of employed persons in industry h of enterprise i; $\sum_r E_r$ is the total number of employed persons in the country; $\sum_r E_r^h$ is the sum of the employment of industry h in all regions of the country; $\sum_i E_h^i$ is the sum of the employed persons of all enterprises in industry h.

We add the three derived mediating variables (i.e., CXZS, IS2 and EG) separately to fit the spatial Durbin model, noted as SDM(1), SDM(2) and SDM(3), respectively.

4.4.4. Regional differences

Given that the natural environment, capital endowment, policy practice and socio-economic development are different between western, central and eastern regions[3] (Liu et al., 2018), the urban LRM model may have different modes of action on GTFP across regions. Therefore, according to the division standards of relevant state departments, the cities were grouped into eastern, central, and western regions according to their geographic locations. Then, the selected spatial econometric model with geographic distance weight, namely Eq. (6), was applied to each city group. In addition, we incorporate all the three mediating variables into each model.

5. Results and discussion

5.1. Description and spatial maps of GTFP and LRM indices

Statistical description of the GTFP and LRM index values (Fig. 3) and key explanatory variables are summarized in Table S1. Overall, the GTFP index value is 0.736 for all the 277 sample cities, with a standard deviation of 0.151 and a wide range of 0.075–1.000. Based on the regional partitioning process, the 277 cities are divided into three groups with 97, 100 and 80 cities for eastern, central, and western regions, respectively.

Comparing three geographic regions, the highest GTFP value of 0.789 is observed in the eastern geographic region, while the values in the western part (0.710) and central region (0.706) are lower. Thus, the eastern region has a greater level of productivity, even accounting for the non-market outputs, than the western and central regions. Compared to the central region, the productivity in the western region is slightly higher probably due to the lower negative outputs that compromise positive outputs. Regarding the key variable of land allocation, the extent to which land resource is misallocated is slightly larger in the eastern region (1.732) than the central region (1.692) and much larger than the western region (1.283), reflecting that local governments in eastern cities are inclined to enlarge investment through land allocation in an inappropriate way.

During 2006–2013, the overall mean GTFP index values for all sample cities experienced an (nearly monotonically) increasing trend, from 0.73 to 0.74 (Fig. 4). Comparatively, in the eastern region, GTFP first increased to a peak around 2010 and then maintain a certain level; GTFP in the central region steadily increased with a small dip in 2012; GTFP in the western region fluctuated until 2010 but then increased to a larger extend afterwards. The trajectories of lnLRM (in absolute value) are generally similar for all sample cities and those by region, declining from 2007 to 2011 and then slightly increasing until 2013.

Fig. 5 shows the spatial patterns of GTFP and LRM indices for the sample cities over the country. Consistent with the statistical outcomes, there is a high-to-low gradient of GTFP index values from east to west. Noticeably, in line with the result from the Moran's I test, more clusters of higher levels of GTFP are observed along the eastern coast, together with a cluster located in the north-central part and a few scattered in central and western regions. Regarding the LRM index value, the cluster pattern is not as prominent as that of GTFP, and exhibits more heterogenous characteristics over space. A few cities with higher degrees of LRM are found in eastern cities (e.g., Shanghai Municipality) and northern cities (e.g., Heilongjiang Province). More cities, particularly those in the central region, have a moderate degree of LRM, while only a few locating in northern-central part have a very low degree of LRM.

5.2. Effects of LRM on GTFP

Empirical results from FEM and SDM show consistent negative effects of land resource misallocation on green total factor productivity, and the effects are statistically significant across all the three models (Table 1). In particular, the spatial lag coefficient (ρ) in the SDM model is significantly far from zero. This result, along with the significant spillover effects of population and urban infrastructure, confirms the appropriateness of selecting the SDM accounting for the spatial effects. Table 2 presents the direct, indirect, and total effects derived from the SDM.

Specifically, in the first fixed-effects model, i.e., FEM-1 without covariates, the effect of ln LRM on GTFP is negative with an estimated coefficient of $-$ 0.007 at the 5% significance level. In FEM-2, which controls other explanatory variables, the effect of ln LRM remains stable with nearly the same direction and magnitude. Moving onto the spatial Durbin model, namely SDM-3, the LRM effect on GTFP is even stronger and more statistically significant with high robustness. According to the coefficient estimation, an increase in every unit of the LRM-relevant index would significantly reduce GTFP level by 0.8%. Moreover, the estimated coefficient for the interaction between LRM index and spatial weight matrix is statistically significant, suggesting that the interacting effects among cities in the spatial domain is substantial. This leads to the significant indirect and significant total effects of LRM on GTFP as shown in Table 2.

These results reveal that the misallocation of land resources can directly undermine the overall GTFP in the cities across the whole country of China. In each city, due to the improper regulations by local governments, the land prices were disproportionately distorted to an extremely low level. The low land price has greatly reduced the cost of industry establishments, attracting a massive group of low-productivity enterprises to enter into the industry zones while squeezing out high-end enterprises (Shao et al., 2016). As a result, the industry-zoning land was crowded by intensified and heavy industries that are often labelled with high pollution, large emission, and huge energy consumption. This is consistent with the findings of Li et al. (2016). The shifted emphasis of developing these highly polluted industries caused serious environmental degradation such as increase in finer particle matters, eventually leading to a huge compromise in non-marketable costs that reduce the total green productivity. Meanwhile, this process of declined productivity due to land misallocation exhibits spillover effects, meaning that strategic interactive behavior among local governments in the competition for growth allows the inhibitory effect of land resource misallocation on GTFP to be transmitted continuously in space, generating significant spatial spillover effects on a larger scale.

[3] With reference to the division of east, middle and west announced by the National Bureau of Statistics of China in January 2017, it is as follows: the eastern region includes 11 provinces (cities) including Guangdong, Hainan, Fujian, Shandong, Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu and Zhejiang; the central region includes 8 provinces including Hubei, Hunan, Shanxi, Jiangxi, Henan, Jilin, Heilongjiang and Anhui; and the western region includes 12 provinces (cities, autonomous regions) including Ningxia, Xinjiang, Gansu, Qinghai, Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shanxi and Tibet. Tibet is not included in the internal list due to lack of data.

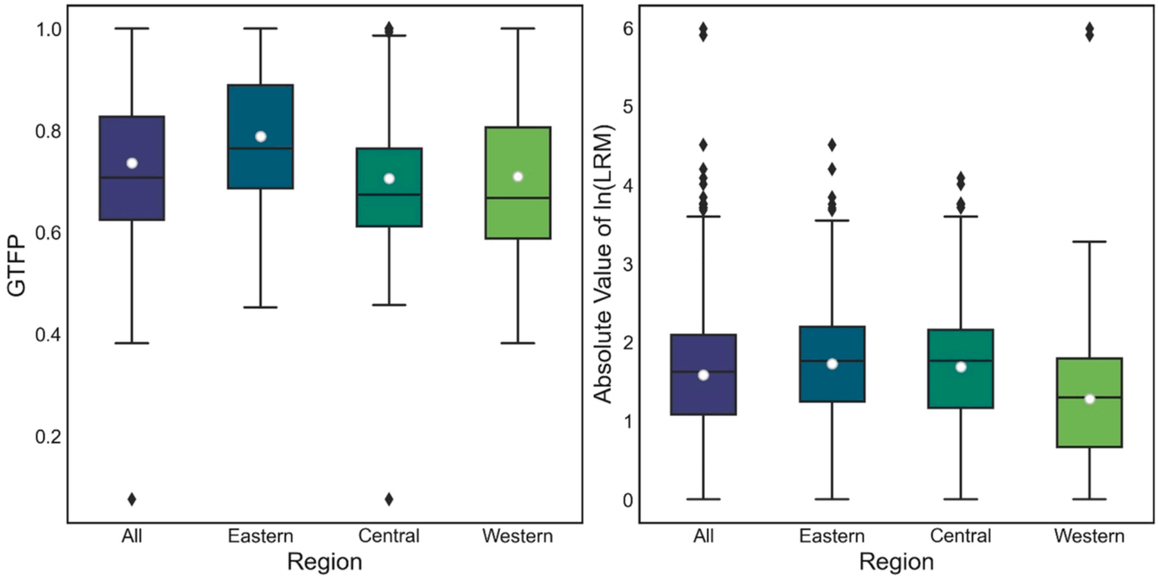

Fig. 3. Distributions of GTFP and lnLRM (absolute value) for all samples and for those by region.

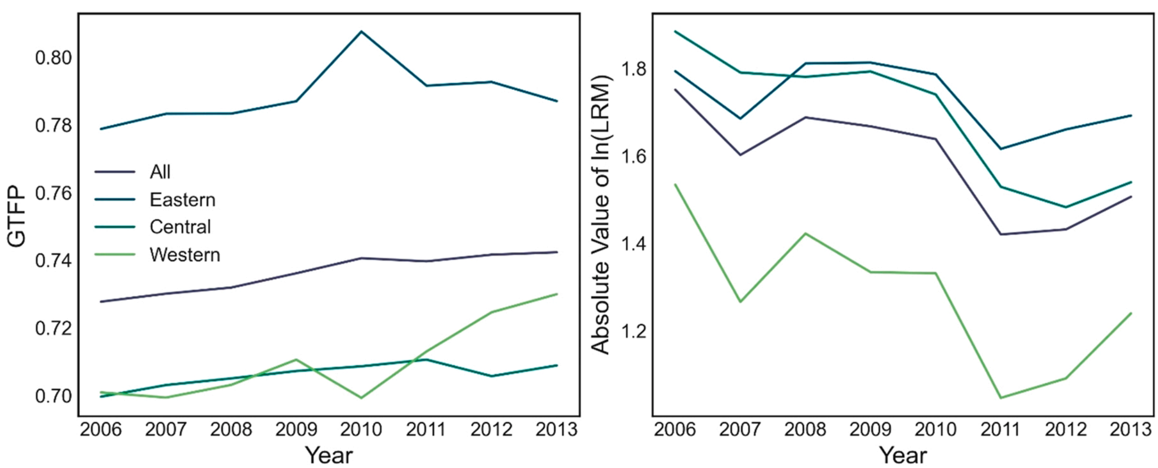

Fig. 4. Trends of GTFP and lnLRM (absolute value) for all samples and for those by region during 2006–2013.

Among the three control variables, large population is the most significant factor that reduces the overall productivity, which is true for all its direct, indirect, and total effects (Table 2). The increase in living residents and/or flowing people could be accompanied by aggravated problems on huge demand of land resources, traffic congestions, environmental deterioration, and other resource scarcity (Chen and Tang, 2019). Such crowd issues as traffic congestion would make the city less attractive for flowing population to settle down, and under the pressure of environmental regulations the establishment of high-emission industries tended to expand to areas covering the surrounding cities. The direct effect of urban infrastructure is marginally statistically significant. The infrastructure development can be viewed as an investment behavior by local governments, where the return rate of capital will decrease and negatively affect the productivity, according to the theory of marginal efficiency of investment (Huang and Chen, 2018). Finally, the effects of human capital as represented by education level are not statistically significant, suggesting its trivial influence for productivity promotion.

5.3. Robust tests

To test the robustness of the estimated effects of LRM on GTFP in the SDM, we performed three major procedures with their corresponding results shown in Table 3. The first approach replaces the measurement of LRM with an alternative indicator. In this study, we derive the proportion of area in land transferred by agreement in total area of available land for trade as a surrogate of LRM. As seen from the first column in Table 3, the LRM effect stays negative and becomes even more significant, while the overall estimation is generally similar to the models in Table 1. The second approach changes the design of the spatial weight matrix. This test selects the gravity model matrix because it offers comprehensive understanding of geographic distances and economic distances in the econometric analysis (Xie et al., 2019). Results from the second column of Table 3 also confirms that the magnitude and significance level of the LRM effect are consistent with those in the SDM.

The third is the System Generalized Method of Moments (SYS-GMM) estimation that considering endogeneity. Although the mismatch of land allocation may be inclined towards the development of intensive and heavy industries that impede GTFP, the change in GTFP can also stimulate the optimization of land allocation, which involves the endogenous relationship. At the same time, due to data availability, unobservable factors may render the correlation between the dependent variable and the error term and bias the coefficient estimation. The third column in Table 3 reveals the SYSGMM estimated outcomes based on

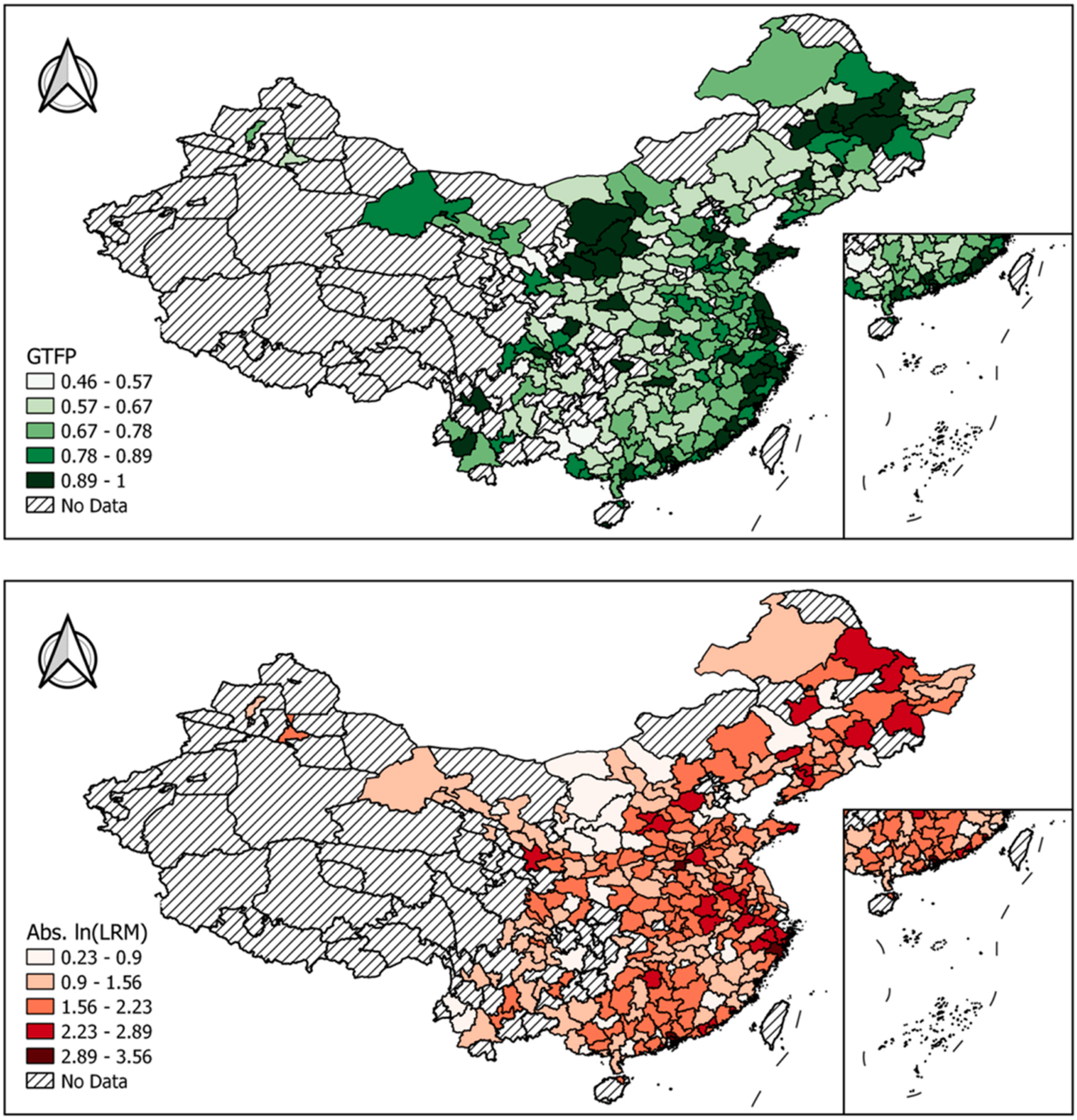

Fig. 5. Maps of mean values of GTFP and lnLRM (absolute value) during 2006–2013.

the geographic distance spatially weighted matrix with endogeneity. Here, the spatial lag term of the mismatch of land resources is used as the explanatory variable and uses the systematic GMM method to estimate in Stata. The estimated parameters have not substantially changed in direction, similar to the SDM outcomes.

5.4. Interaction effects of LRM with mediating factors on GTFP

Table 4 presents results that reveal the direct, indirect, and total effects between LRM and the three mediating factors. The coefficients of the interaction item (ln *LRM** ln *CXZS*) of land resource mismatch and urban innovation capacity are -0.074($p < 0.10$) and -0.073 ($p < 0.10$) for the indirect and total effect, respectively. This shows that the hypothetical variable has a significant overall effect on how land resource mismatch on GTFP. Therefore, Hypothesis 2a (H2a) is confirmed.

The direct effect of the land resource mismatch and the industrial structure interaction term (ln *LRM** ln *IS*2) is significantly negative, suggesting that the mismatch of land resources has weakened the role of industrial structure in promoting GTFP. Thus, Hypothesis 2b (H2b) is confirmed.

The interaction term of land resource mismatch and manufacturing agglomeration (ln *LRM** ln *EG*) does not reveal significant effects on GTFP. The current Chinese manufacturing agglomeration model is not perfect, so that the effects of economy of scale and technology spillovers cannot be effectively manifested with a trivial impact on GTFP.

Table 1
Estimated results of spatial econometric models.

Variable	FEM (1)	FEM (2)	SDM (3)
ln *LRM*	-0.007**	-0.007**	-0.008***
	(−2.360)	(−2.400)	(−2.726)
ln *P*	/	-0.121***	-0.078*
		(−3.030)	(−1.662)
ln *EDU*	/	-0.023*	-0.001
		(−1.880)	(−0.096)
ln *PURL*	/	0.002	-0.014**
		(0.390)	(−2.266)
*W** ln *LRM*	/	/	-0.081*
			(−1.941)
*W** ln *P*	/	/	-2.395***
			(−6.242)
*W** ln *EDU*	/	/	0.078
			(0.638)
*W** ln *PURL*	/	/	0.162*
			(1.905)
ρ	/	/	0.714***
			(11.139)
Log-likelihood	/	/	3094.457
Number of observations	2216	2216	2216
Number of cities	277	277	277
R-square	0.003	0.009	0.844

Note: t-statistics are shown in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 2
Different types of effect derived from SDM.

Variable	Direct effect	Indirect effect	Total effect
ln *LRM*	-0.008***	-0.313*	-0.322*
	(−3.110)	(−1.735)	(−1.775)
ln *P*	-0.113**	-9.011***	-9.125***
	(−2.474)	(−3.281)	(−3.318)
ln *EDU*	0.000	0.285	0.285
	(0.012)	(0.632)	(0.632)
ln *PURL*	-0.012*	0.554	0.542
	(−1.860)	(1.612)	(1.568)

Note: values in parentheses are t-statistics. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3
Robust test outcomes.

Variable	Proportion of land transferred by agreement	Gravity model matrix	SYS-GMM
ln *LRM*	-0.022***	-0.006**	-0.003*
	(−3.110)	(−2.264)	(−2.130)
ln *P*	-0.150***	-0.117***	-0.002
	(−3.600)	(−2.597)	(−0.070)
ln *EDU*	-0.019	0.001	0.009
	(−1.590)	(0.088)	(1.020)
ln *PURL*	-0.002	-0.017***	-0.008*
	(−0.250)	(−2.581)	(−1.900)
*W** ln *LRM*	/	-0.027	0.031
		(−1.274)	(1.530)
*W** ln *P*	/	-2.541***	-0.379
		(−7.386)	(−1.260)
*W** ln *EDU*	/	-0.004	0.152
		(−0.051)	(1.410)
*W** ln *PURL*	/	0.073	0.170**
		(1.468)	(2.530)
Sargan test	/	/	25.380
			[0.013]
Hansen test	/	/	11.710
			[0.469]
AR(1) test	/	/	-2.610
			[0.009]
AR(2) test	/	/	-1.580
			[0.469]
Sample size	2216	2216	1939

Note: The SYS-GMM estimation in this study is done with the "xtabond2" program; all regression models are Two-step; endogenous variables are ln *LRM*and *W** ln *LRM*; t-statistics are in parentheses; adjoint probability is in square brackets. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

5.5. Regional heterogeneity

A further region-level analysis shows heterogeneous outcomes of the LRM effects on GTFP among the western, central, and eastern regions (Table 5 and Table S2). In the eastern region, compared with the direct effect that is significant, the indirect effect is much stronger and more significant, with the coefficient of − 0.598 at the 1% significance level. These cities have been undergoing increased frequency of industrial land transfer, resulting in relatively poor coordination between spatial allocation of land and overall productivity. As the local governments were also under pressure of various environmental regulation initiatives by the central government, most low-efficiency and high-consumption industries have been forced to relocate in surrounding cities of these major developed cities. The interaction between LRM and CXZS has significant indirect and total effects, both of which are positive, suggesting in the eastern region, Hypothesis 2a (H2a) is not confirmed. By the same token, Hypothesis 2b (H2b) has not been confirmed. For the interaction between LRM and EG, all the three types of effect are not statistically significant.

In the central areas, the direct, indirect, and total effects of LRM are all significantly negative on GTFP. Attributed mainly to "The Rise of Central China" strategy,[4] land trade under agreement became a major means for regional governments to strengthen their expenditure performance. As these governments increasingly rely on land finance, the associated degree to which land is misallocated also disproportionately rises, deteriorating the overall green productivity in the city itself as well as the cities nearby. The mismatch of land resource allocation can further weaken the overall productivity through indirectly hindering the innovation capacity in the central cities. The interaction between LRM and CXZS has the same significant negative indirect effect and total effect. Thus, Hypothesis 2b (H2b) and Hypothesis 2c (H2c) has not been confirmed.

Last, in the western region, the direct effect of LRM on GTFP is significantly negative. There still exists a huge gap between the western region with the central and eastern regions in terms of fundamental infrastructure, making the cities fall behind in economy and remain in the early stage of industrialization (Xie et al., 2019). The less-developed land market has also made it difficult to fully implement the land use policies on industrial transformation on a large scale, causing low total green productivity. However, the indirect effect of LRM on GTFP is significantly positive. This suggests that in terms of urban land allocation, the biased allocation of local land resources in the industrial sector may allow polluting industries in neighboring cities to keep moving inward for land rent preferences and agglomeration effects, thus increasing the GTFP of neighboring cities. In addition, we detect that the negative effect of LRM on GTFP can be slightly, albeit directly, offset by increase in IS2; however, the indirect effect of LRM could be enhanced by industrial structure through spillover effects. This result reflects that, in each city, the industrial structure under the support by policies can facilitate the overall green productivity but may indirectly hinder the productivity through influencing the surrounding cities due to the prohibitive cost of industrial restructuring in a shorter run.

5.6. Limitations and future directions

Although the data of China Urban Statistical Yearbook is incomplete due to the unpublished data of individual cities (such as Lhasa, Sansha, Zhongwei) or the lack of index data in published cities, they are the only official certified data with samples covering most cities in China, which

[4] Website: www.gov.cn/zhengce/content/2012–08/31/content_1147.htm/

Table 4
Estimated outcomes of models for influencing mechanisms of LRM on GTFP.

Variable	SDM (1)			SDM (2)			SDM (3)		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
ln *LRM*	-0.007***	-0.240**	-0.247**	0.125***	1.045	1.170	-0.019**	-0.605*	-0.624*
	(−2.729)	(−2.117)	(−2.173)	(3.359)	(0.808)	(0.901)	(−2.151)	(−1.836)	(−1.885)
ln *LRM** ln *CXZS*	0.000	-0.074*	-0.073*	/	/	/	/	/	/
	(0.236)	(−1.739)	(−1.723)						
ln *LRM** ln *IS*2	/	/	/	-0.034***	-0.321	-0.355	/	/	/
				(−3.540)	(−0.948)	(−1.043)			
ln *LRM** ln *EG*	/	/	/	/	/	/	-0.001	-0.039	-0.040
							(−1.241)	(−1.250)	(−1.281)
ln *P*	-0.091**	-7.617***	-7.708***	-0.092**	-6.275***	-6.367***	-0.100**	-6.136***	-6.237***
	(−2.132)	(−3.661)	(−3.696)	(−2.138)	(−3.778)	(−3.835)	(−2.271)	(−4.093)	(−4.161)
ln *EDU*	-0.003	0.377	0.373	0.009	0.241	0.250	-0.001	0.158	0.157
	(−0.282)	(1.241)	(1.230)	(0.873)	(0.857)	(0.895)	(−0.108)	(0.531)	(0.528)
ln *PURL*	-0.013**	0.383*	0.370*	-0.017***	0.416*	0.398*	-0.012**	0.457**	0.445*
	(−2.099)	(1.717)	(1.655)	(−2.928)	(1.898)	(1.812)	(−2.069)	(1.965)	(1.905)

Note: t-statistics are shown in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01.

Table 5
Estimation results of models for regional heterogeneity.

Region	Effect	ln *LRM*	ln *LRM** ln *CXZS*	ln *LRM** ln *IS*2	ln *LRM** ln *EG*
Eastern region	Direct	-0.123**	0.000	0.031**	0.000
		(−2.045)	(0.149)	(2.091)	(0.390)
	Indirect	-0.598***	0.017***	0.139***	0.000
		(−3.155)	(3.070)	(3.001)	(0.013)
	Total	-0.721***	0.017***	0.170***	0.000
		(−3.582)	(2.905)	(3.469)	(0.118)
Central region	Direct	-0.293***	-0.004	0.075***	-0.000
		(−7.179)	(−1.506)	(7.528)	(−0.030)
	Indirect	-0.583**	-0.030**	0.143**	-0.008
		(−2.531)	(−2.431)	(2.557)	(−1.420)
	Total	-0.876***	-0.034***	0.218***	-0.008
		(−3.550)	(−2.603)	(3.639)	(−1.317)
Western region	Direct	-0.162**	0.001	0.031*	-0.003*
		(−2.246)	(0.151)	(1.821)	(−1.758)
	Indirect	0.263*	-0.011	-0.069*	0.003
		(1.721)	(−1.614)	(−1.822)	(0.876)
	Total	0.101	-0.010	-0.037	-0.000
		(0.629)	(−1.576)	(−0.962)	(−0.016)

Note: t-statistics are shown in parenthesis. * p < 0.1; ** p < 0.05; *** p < 0.01.

can comprehensively reflect the economic and social development of Chinese cities (Han et al., 2020; Zhou et al., 2020). In addition, when initiating this research, the data on Chinese industrial enterprises were only updated to 2013, thus limiting our data regression until the year of 2013. The database of Chinese industrial enterprises is now updated to 2014 and can be used in further research.

At present, the basis for the choice of the spatial weight matrix is mostly empirical. The assignment rule of the adjacency matrix is that a space sample that has a common boundary and a common vertex with a space sample can be defined as its adjacent unit. The spatial weight matrix method with geographic distance assumes that the strength of spatial interaction depends on the distance between the geo-locations of regional administrative units. Compared to the adjacent matric assignment that is based on adjacent units sharing common boundaries and vertexes, the geographic distance matrix is better at manifesting economic interdependences between urban units. Different spatial weight matrix models (e.g., economic weight matrix model) can be used in future studies for robustness testing.

The division standards for the eastern, central, and western regions are not uniform. In terms of geographical location, Inner Mongolia and Guangxi autonomous regions should belong to the central region. However, from the perspective of economic development level, the per capita GDP level of Inner Mongolia and Guangxi autonomous regions is just the same as that of the western 10 provinces (municipalities and autonomous regions), but there is a certain gap with other central regions. Inner Mongolia and Guangxi were added to the preferential policy of "Western Development" formulated by the country in 2000. The current classification standard is based on the long-term evolution of its economic development level and geographical location. This research divides cities into eastern, central, and western regions according to the classification standard announced by the National Bureau of Statistics of China in January 2017. However, in the future exploration is not necessarily limited to the East, Central and West regional division, but can be dependent on the size of the city or the level of urban economic development or be further subdivided into seven regions, such as Northeast, North, Central, South, East, Northwest, and Southwest.

6. Conclusion and policy implication

The behavior of land resource allocation is not only a typical phenomenon in China, but also an important part of the social and economic development in other countries worldwide, especially in developing countries. For example, Chen (2017) and Britos et al. (2022) both found that the prevalence of untitled land in developing countries (e.g., Guatemala) is an important reason to explain the gap in agricultural productivity between developed and developing countries, and the imperfect land market will lead to the decline of total agricultural productivity. Their research further reflects the importance of the allocation of land resources in affecting the overall productivity of the country. Thus, the examination of China's overall productivity considering non-market values with the focus on land allocation can be informative for addressing the sustainability issues across the globe, particularly in the developing world where such needs are urgent. Based on a dataset of 277 cities in China, this study investigates how land resource misallocation (LRM) impact urban green total factor productivity (GTFP) and explores the associated mechanisms as well as regional heterogeneity. According to the spatial Durbin estimation, we find that the misallocation of land resources can directly reduce green total factor productivity, with significant spillover effects. LRM is found to influence GTFP mainly through hindering innovation capacity (CXZS) and changing industrial structure (IS2). There exist substantial regional differences among the eastern, western, and central cities regarding the effects of LRM on GTFP. Therefore, the main concluding remarks include that the misallocation of land resources is a major reason for the decline in the overall green productivity that accounts for energy consumption and environmental degradation, which involves various pathways and reflects heterogeneous effects across geographic regions. To eliminate obstacles that hinder the productivity growth and minimize the non-market costs due to energy consumption and environmental degradation, both central government and local governments should lay stress onto the appropriate allocation of land resources during the processes of urbanization, industrialization, and modernization. Based on the robust results derived from the model estimation, policy implication can be provided to inform policymakers, environmentalists, and land planners for future policy designs as well as practice initiatives for enhancing productivity in a benign and sustainable way. Policy suggestions regarding land use planning are as follows.

In the conceptual framework, we formulated Hypothesis 1 about land resource mismatch directly reduces GTFP and it was verified in the empirical analysis. Due to the relatively low price of land allocated by the government, the misallocation of land resources directly reduces the GTFP of firms by allowing more low-productivity firms with higher pollution and emissions to participate in the land market. Therefore, one suggestion is to allocate land resources rationally and alleviate the local government's control over land use. Letting land resources be optimally allocated in the market and enterprises with lower pollution and higher productivity get more land use, GTFP would be improved following reduced pollutant emissions. The transformation from the original participants and benefit-sharers to supervisors, guides, and services can change the way of land resource allocation from government-led to market-led, downplaying the importance of GDP in performance evaluation and reducing the distortion in the allocation of land resources. Meanwhile, policymakers need to strength investment in environmentally friendly enterprises and encourage the development of "clean and innovative" enterprises in land use planning for industrial development.

According to SDM(1) and SDM(2) models, we have verified Hypotheses 2a and 2b. Land resource mismatch reduced urban GTFP by inhibiting technological innovation and industrial structure upgrading mechanisms. The mismatch of land resources will bias the allocation of land resources to enterprises with low technological innovation efficiency and industrial structure sticking to the characteristics of rough and loose, so that enterprises with high innovation efficiency and belonging to modern service industry are not reasonably allocated to land. When there is no mismatch, the allocation of land resources can be optimized, and enterprises with strong innovation and tertiary industries can get more land use, thus enhancing the motivation of enterprises to conduct technological innovation and further optimizing the industrial structure. Therefore, this finding leads to the recommendation of allocating more land to enterprises with strong innovation capacity and industrial structure mostly favoring modern service industry. Based on optimizing the land resource allocation model, it is suggested to increase the investment in scientific research and stimulate enterprises to make technological innovation and guide them to develop technological innovation in a green direction. In addition, it is necessary to implement energy conservation and emission reduction, improve the production efficiency and energy utilization rate of enterprises, and then promote the upgrading of the industrial structure. Policymakers should not only promote the construction of institutional environment, increase the investment in innovative and environmentally friendly enterprises, but also strengthen the supervision and guidance of excessive market competition to reduce the resistance to the improvement of urban green productivity, effectively alleviating the negative effect of the mismatched channel variables of land resources.

In the literature review, we summarized previous studies on GTFP regional heterogeneity. The empirical results of this study also showed significant regional differences between eastern, western, and central cities. In the eastern and central regions, land resource mismatch not only has a dampening effect on the GTFP of the region, but also on the surrounding areas. This is not the case in the western region, where land resource mismatch directly reduces the GTFP of the region, but has a positive spillover effect on the GTFP of neighboring cities. Therefore, when implementing land use policies, the government should tailor them to local conditions and develop different land allocation policies according to different regional characteristics. In the eastern and central regions, attention should be paid to both the negative impact effects of the region and the surrounding areas. The scale of land use should be allocated scientifically and reasonably according to local advantageous industries, and the layout and progress of construction land should be effectively controlled to prevent external uneconomic land use. In addition, it is worthwhile to consider the spillover effects on neighboring areas and adjust land policies to reduce the impact on neighboring cities. The western region witnesses that the mismatch of land resources directly reduces GTFP in the region. Land resource allocation in this region should reduce the biased allocation to industrial enterprises and control the transfer of polluting enterprises from surrounding areas.

Declaration of Conflicting Interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Data Availability

We have included the code used in this study in the attached file. Data are available upon request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.landusepol.2022.106353.

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