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Research Article

Coordinated Development of Urban Land Use and Ecological Economics in China

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To analyze the coordination between land use and the ecological economy in China, ecoefficiency and land use intensity were measured using the nonradial, nonoriented slacks-based measure (SBM) and the vertical and horizontal scatter degree method. The TOPSIS method was then used to comprehensively evaluate regional differences in coordination. Our research indicates that the level of coordinated development between intensive urban land use and the ecological economy in China showed an overall upward trend from 2006 to 2017. The level of coordination was high in Beijing, Shanghai, and Tianjin and was low in Gansu, Ningxia, and Xinjiang. Changes in ecoefficiency were not consistent with the degree of coordination, and intensive urban land use was positively correlated with the level of coordination, which showed a mutually reinforcing relationship. Improving ecoefficiency is necessary for intensive urban land use, and for ecological improvement, coordinated development between ecoefficiency and urban land use intensity is essential. The establishment of environmentally friendly land use patterns could promote urban land use.

1. Introduction

Present urban land use in China, which has experienced an acceleration of industrialization and urbanization, directly affects urban economics, social development, and the construction of human settlements. When considering urban land use, ecological functions are typically ignored in favor of economic and social functions. The depletion of natural resources and overextension of environmental carrying capacity caused by urban land expansion have seriously hindered the development of urbanization in China. Construction on urban land in China increased from 6720 km^2 in 1986 to 49,983 km^2 in 2014, with an average annual growth rate of 7.43%. The first national pollution bulletin showed that China's industrial emissions of sulfur dioxide and soot were 21,197,500 and 11,666,400 tons, respectively, accounting for 91.4% and 84.2% of total pollution emissions. The direct economic loss caused by the destruction of natural resources and the environment is substantial. The importance of land use regulations should not be ignored in the pursuit of ecological development.

Coordination between intensive urban land use and ecological economics can also be conceived of as coordination among internal components of urban economic, social, and ecological development during the process of urbanization. Research on the relationship between intensive urban land use and ecological economics has concentrated mainly on urban land use and ecology in a single region; aspects that have been considered include the effects of intensive land use [1, 2], the ecoefficiency of land use [3–5], the impact of ecology on intensive land use [6, 7], and the relationships among these aspects [8, 9]. With continuing urbanization, research efforts are increasingly being devoted to the study of regional development, in three main respects: (1) the relationship between economic development and the ecological environment, (2) the relationship between land expansion and population growth, and (3) the coordination of the internal unit of urbanization. For

example, using spatial lag, spatial error, and spatial Durbin models, Tang et al. analyzed the relationship between urban land and regional economic development at the county level in the Beijing–Tianjin–Hebei region, based on analysis of cross-sectional data from 2015 [10]. Lv et al. empirically analyzed the interaction between land urbanization and population urbanization in Nanchang from 2002 to 2017 using the coupling coordination model (CCM) [11]. Cui developed a "comprehensive coordinated development index" for an urbanization–resources–environment (URE) system (URECDI) to represent the relationships among urbanization, resources, and environmental subsystems [12]. Liu et al. stated that the interaction among urban economic, social, and ecological systems in China, at the prefecture level and above, could be modeled using a CCM. Their results showed that coordinated urban development in China is spatially heterogeneous [13].

These studies provide a basis for further exploration of regional coordinated development. From a quantitative and dynamic perspective, there are few studies that focus on the coordinated relationship between land use and ecological development and propose effective regulatory approaches.

During the process of urbanization, can ecological improvement and intensive use of urban land coexist? Also, how strongly do they interact? To answer these questions, we empirically studied ecological efficiency in the context of intensive urban land use and provide suggestions for its optimization.

2. Evaluation Index System and Data Sources

2.1. Evaluation Index System Construction. Intensive urban land use is a dynamic and complex process related to the level of economic development and scientific and technological progress. The basic aim is to increase the input of elements per unit area and optimize the structural layout, to improve the utilization rate of urban land for greater economic, social, and environmental benefits. Based on the research of Zhang et al. [14–17], the following indicators of intensive urban land use were selected for this study: per capita fixed asset investment; number of employees in secondary and tertiary industries; per capita gross domestic product (GDP); per capita fiscal revenue; per capita construction land; per capita total retail sales of social consumer goods; per capita road area; per capita green space area; the green coverage rate of the built-up area; and population density.

According to the definition of ecoefficiency of the World Business Council for Sustainable Development (WBCSD) [18], which is based on the environmental and economic situation of Germany and the regional ecological efficiency evaluation index system constructed by Zhang [19] and Seppälä [20], resource consumption is the main index of ecological efficiency. The most important resources consumed are energy, water, land, and minerals. Seppälä [20] suggested that GDP, industrial added value, and total product value could be used as indicators of economic value in ecoefficiency analysis. To determine the overall developmental level of a region, the desirable output index (represented by GDP) was used, based on the constant price in 2000. Three indicators for environmental pollution and ecological destruction were used: (1) wastewater emissions, (2) industrial SO_2 emissions, and (3) smoke (powder) dust emissions.

2.2. Data. All the data were collected from the China Statistical Yearbook (2007–2018) and China urban statistical yearbook (2007–2018). Considering availability of the data, Tibet, Hong Kong, Macao, and Taiwan are not included in our data collection. We set the research period from 2006 to 2017.

3. Research Methods

3.1. Vertical and Horizontal Scatter Degree Method. Urban land use intensity is a dynamic phenomenon that changes continuously with time. The measurement of urban land use intensity should not only reflect the state of land use intensity at a certain cross-sectional moment in each evaluation area but should also describe the changing trends of urban land across time. The vertical and horizontal scatter degree method is an evaluation method based on a multidimensional time series table that is used to determine weights [21]. It not only reflects the "horizontal" level of intensity in all study areas at different times but also reflects the "vertical" intensity of each area. The intensity status at different times can be determined by comprehensively considering the maximization of differences between "horizontal" and "vertical" land intensification, which will reflect the differences between the evaluated objects.

Table 1, referred to as a multidimensional time series data table, shows the data from the evaluation indices in different regions at different times. Here, $t_i\,(i = 1, 2, \ldots, N)$ represents time, $S_i\,(i = 1, 2, \ldots, n)$ represents geographic regions, and $x_i\,(i = 1, 2, \ldots, m)$ represents the evaluation indices.

The dynamic comprehensive evaluation function supported by Table 1 is

$$y_i(t_k) = \sum_{j=1}^{m} w_j x_{ij}(t_k), \quad k = 1, 2, \ldots, N,\ i = 1, 2, \ldots, n, \tag{1}$$

where $y_i(t_k)$ is the comprehensive evaluation value of city S_i at time t_k and w_j is the weight coefficient.

The overall difference for each object in the multidimensional time series data table is expressed as the sum of the total deviation of squares of $y_i(t_k)$:

$$\sigma^2 = \sum_{k=1}^{N}\sum_{i=1}^{n}\left(y_i(t_k) - y\right)^2. \tag{2}$$

After standardizing the original data, we get $\overline{y} = 0$; hence,

$$\sigma^2 = \sum_{k=1}^{N}\sum_{i=1}^{n}\left(y_i(t_k)\right)^2 = \sum_{k=1}^{N} w^T H_k w = w^T \sum_{k=1}^{N} H_k w = w^T H w, \tag{3}$$

where $w = (w_1, w_2, \ldots, w_m)^T$, $H = \sum_{k=1}^{N} H_k$, and $H_k = A_k^T A_k$,

$$A_k = \begin{pmatrix} x_{11}(t_k) & x_{12}(t_k) & \cdots & x_{1m}(t_k) \\ x_{21}(t_k) & x_{22}(t_k) & \cdots & x_{2m}(t_k) \\ \cdots & \cdots & \cdots & \cdots \\ x_{n1}(t_k) & x_{n2}(t_k) & \cdots & x_{nm}(t_k) \end{pmatrix}, \quad k = 1, 2, \ldots, N. \tag{4}$$

If $w^T w = 1$ is limited, when w is the (standard) eigenvector corresponding to the maximum eigenvalue of H, σ^2 is the maximum, and $\max_{\|w\|} w^T H w = \lambda_{\max}(H)$. When the element of H_k is greater than 0, there must be an element of H greater than 0 and a positive weight coefficient vector. Therefore, the normalized eigenvector corresponding to $\lambda_{\max}(H)$ is the weight vector w.

3.2. SBM Model. Regional development can lead to economic growth, but can also have a negative impact on the environment. For example, water and soil pollution can be classified as "undesirable outputs." There are five main methods for modeling undesirable outputs. The first is to treat pollutants as inputs [22, 23]. The second is hyperbolic measurement [24]. The third method involves converting undesirable outputs into new variables [25]. However, these methods do not reflect actual production processes [26]. Chung et al. proposed a directional distance function approach, which has been adopted by many researchers [27]. The fifth method is the nonradial slacks-based measure (SBM). Traditional radial efficiency measures may introduce error as they neglect slack variables [28]. Hence, a series of models considering the nonradial, nonoriented SBM have been proposed [29–31].

The SBM is described as follows [30]: Suppose there are n homogeneous decision-making units (DMUs) and each DMU has three factors—inputs $x \in R^m$, desirable outputs $y^g \in R^{s_1}$, and undesirable outputs $y^b \in R^{s_2}$. The three matrices are defined as

$$\begin{aligned} X &= (x_1, x_2, \ldots, x_n) \in R^{m\times n}, \quad x_i \in R^m, \\ Y^g &= (y_1^g, y_2^g, \ldots, y_n^g) \in R^{s_1\times n}, \quad y_i^g \in R^{s_1}, \\ Y^b &= (y_1^b, y_2^b, \ldots, y_n^b) \in R^{s_2\times n}, \quad y_i^b \in R^{s_2}. \end{aligned} \tag{5}$$

Here, $x_i > 0$, $y_i^g > 0$, $y_i^b > 0$. Under the situation of constant return to scale (CRS), the production possibility set (PPS) is as follows:

$$P(x) = \left\{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, \lambda \geq 0\right\}. \tag{6}$$

Here, λ is a nonnegative multiplier vector. Based on the PPS, the SBM model considering undesirable outputs can be expressed as

$$\rho^* = \frac{1 - (1/m)\sum_{i=1}^{m}(s_i^-/x_{io})}{1 + (1/s_1 + s_2)\left(\sum_{r=1}^{s_1} s_r^g/y_{ro}^g + \sum_{r=1}^{s_2} s_r^b/y_{ro}^b\right)},$$

$$s.t. \begin{cases} x_o = X\lambda + s^-, \\ y_o^g = Y^g\lambda - s^g, \\ y_o^b = Y^b\lambda + s^b, \\ s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0. \end{cases} \tag{7}$$

3.3. TOPSIS Method. The maximum "positive intensive land use index" and "regional ecological efficiency index" values are obtained for each province. The minimum negative index value is taken as the positive ideal solution (that is, the optimally coordinated state). The minimum value is selected from the positive index, and the maximum value from the negative index is taken as the negative ideal solution (least well-coordinated state). The proximity of each province to the positive ideal solution obtained by the TOPSIS algorithm defines the level of coordination between intensive urban land utilization and the ecological economy in that province (see [32] for details of the TOPSIS algorithm).

4. Results

4.1. Intensive Land Use. China is divided into four main economic regions: east, central, west, and northeast. The eastern region includes Beijing, Fujian, Guangdong, Hebei, Jiangsu, Shandong, Shanghai, Tianjin, and Zhejiang. The central region includes Anhui, Henan, Hubei, Hunan, Jiangxi, and Shanxi. The western region includes Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, and Yunnan. The northeastern region includes Heilongjiang, Jilin, and Liaoning.

Using the vertical and horizontal scatter degree method, the land use intensity of 30 provinces in China was measured for the period 2006–2017 (Table 2). Intensive urban land utilization, in China as a whole and in all four economic regions, showed an overall upward trend, although intensive land use decreased significantly after 2009, which was related to the national macrocontrol policy. A series of stimulus policies introduced by the Chinese government in response to the financial crisis further accelerated the pace of urban expansion, thereby reducing the intensity of urban land use. Intensive urban land use increased most rapidly from 2006 to 2009, by 32.6%. Spatially, the level of intensive land use in China fluctuated between 2006 and 2017. Intensive urban land use decreased in all four main economic regions, although it was still seen in parts of the eastern region, especially Shanghai and Beijing. Intensive land use was also seen in Zhejiang, Shandong, Fujian, Jiangsu, and Hebei, with an annual average of more than 0.5. Urban land use was less intensive in Jilin, Heilongjiang, Gansu, Ningxia, and

Table 1: Multidimensional time series data table.

Region	t_1 $x_1 x_2, \ldots, x_m$	t_2 $x_1, x_2, \ldots, x_m$	$\cdots$ $\cdots$	t_N $x_1, x_2, \ldots, x_m$
S_1	$x_{11}(t_1), x_{12}(t_1), \ldots, x_{1m}(t_1)$	$x_{11}(t_2) x_{12}(t_2), \ldots, x_{1m}(t_2)$	$\cdots$	$x_{11}(t_N) x_{12}(t_N), \ldots, x_{1m}(t_N)$
S_2	$x_{21}(t_1) x_{22}(t_1). \ldots, x_{2m}(t_1)$	$x_{21}(t_2) x_{22}(t_2), \ldots, x_{2m}(t_2)$	$\cdots$	$x_{21}(t_N) x_{22}(t_N), \ldots, x_{2m}(t_N)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_n	$x_{n1}(t_1) x_{n2}(t_1), \ldots, x_{nm}(t_1)$	$x_{n1}(t_2) x_{n2}(t_2), \ldots, x_{nm}(t_2)$	$\cdots$	$x_{n1}(t_N) x_{n2}(t_N), \ldots, x_{nm}(t_N)$

Table 2: Values of urban land intensive use in China (2006–2017).

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.52	0.52	0.61	0.63	0.64	0.64	0.70	0.64	0.61	0.63	0.63	0.65
Tianjin	0.48	0.48	0.56	0.55	0.52	0.62	0.63	0.63	0.61	0.60	0.64	0.64
Hebei	0.43	0.43	0.54	0.39	0.38	0.43	0.45	0.45	0.45	0.44	0.45	0.46
Shanxi	0.34	0.39	0.39	0.41	0.40	0.44	0.46	0.45	0.48	0.47	0.46	0.47
Inner Mongolia	0.27	0.35	0.37	0.39	0.38	0.39	0.42	0.42	0.46	0.49	0.46	0.49
Liaoning	0.31	0.34	0.36	0.36	0.33	0.34	0.36	0.36	0.37	0.33	0.34	0.35
Jilin	0.22	0.25	0.27	0.26	0.25	0.27	0.28	0.29	0.28	0.31	0.31	0.33
Heilongjiang	0.14	0.21	0.20	0.24	0.25	0.29	0.31	0.31	0.32	0.30	0.32	0.34
Shanghai	0.57	0.68	0.54	0.57	0.58	0.62	0.64	0.63	0.64	0.62	0.65	0.66
Jiangsu	0.61	0.60	0.64	0.61	0.56	0.55	0.55	0.53	0.52	0.51	0.52	0.54
Zhejiang	0.59	0.54	0.54	0.51	0.56	0.49	0.52	0.52	0.50	0.50	0.50	0.52
Anhui	0.31	0.38	0.47	0.44	0.44	0.45	0.50	0.48	0.47	0.51	0.52	0.54
Fujian	0.64	0.56	0.61	0.60	0.56	0.54	0.60	0.60	0.61	0.58	0.60	0.61
Jiangxi	0.46	0.45	0.52	0.50	0.47	0.43	0.51	0.51	0.44	0.47	0.48	0.47
Shandong	0.49	0.60	0.57	0.55	0.56	0.53	0.55	0.54	0.52	0.51	0.53	0.53
Henan	0.42	0.50	0.42	0.51	0.52	0.51	0.54	0.53	0.54	0.55	0.57	0.57
Hubei	0.33	0.42	0.46	0.40	0.39	0.40	0.42	0.43	0.43	0.42	0.43	0.44
Hunan	0.44	0.45	0.51	0.49	0.48	0.49	0.54	0.54	0.55	0.57	0.59	0.60
Guangdong	0.51	0.52	0.53	0.51	0.53	0.51	0.52	0.53	0.52	0.51	0.54	0.56
Guangxi	0.36	0.41	0.43	0.40	0.43	0.44	0.48	0.45	0.41	0.44	0.43	0.45
Hainan	0.39	0.43	0.38	0.38	0.40	0.43	0.48	0.45	0.38	0.44	0.45	0.46
Chongqing	0.29	0.31	0.41	0.44	0.44	0.46	0.45	0.48	0.44	0.42	0.45	0.48
Sichuan	0.39	0.47	0.38	0.41	0.38	0.39	0.41	0.51	0.46	0.46	0.46	0.47
Guizhou	0.38	0.32	0.45	0.43	0.38	0.43	0.42	0.41	0.40	0.43	0.44	0.45
Yunnan	0.41	0.44	0.49	0.48	0.48	0.48	0.52	0.52	0.49	0.40	0.46	0.49
Shaanxi	0.43	0.41	0.32	0.30	0.37	0.41	0.40	0.43	0.43	0.42	0.44	0.46
Gansu	0.31	0.28	0.25	0.25	0.26	0.26	0.28	0.31	0.31	0.33	0.34	0.36
Qinghai	0.31	0.35	0.39	0.38	0.39	0.42	0.50	0.43	0.39	0.42	0.41	0.44
Ningxia	0.10	0.28	0.26	0.25	0.28	0.29	0.26	0.25	0.30	0.28	0.31	0.32
Xinjiang	0.26	0.30	0.32	0.27	0.27	0.27	0.28	0.28	0.30	0.29	0.31	0.33
China	0.39	0.42	0.44	0.43	0.43	0.44	0.47	0.46	0.45	0.45	0.47	0.48
East	0.52	0.54	0.55	0.53	0.53	0.54	0.56	0.55	0.54	0.53	0.55	0.56
Central	0.38	0.43	0.46	0.46	0.45	0.45	0.49	0.49	0.48	0.50	0.51	0.52
West	0.31	0.34	0.35	0.35	0.36	0.38	0.39	0.40	0.38	0.38	0.40	0.42
Northeast	0.22	0.26	0.28	0.29	0.28	0.30	0.31	0.32	0.33	0.31	0.32	0.34

Data are calculated according to equation (1).

Xinjiang, but showed a rapidly increasing trend in the latter two regions (average annual growth rate >3.2%).

In summary, intensive urban land use in China increased significantly between 2006 and 2017. Urban land use intensity was the highest in the eastern region, but showed a rapidly increasing trend in the central and western regions. Urban land use intensity was relatively low in the northeastern region.

4.2. Measurement of Regional Ecoefficiency. The regional ecoefficiency of 30 provinces in China was calculated for the period 2006–2017 using DEA Solver Pro5.0 software (Saitech Inc., Fremont, CA, USA) (Table 3). During this period, regional ecoefficiency showed a fluctuating trend (i.e., improvement followed by deterioration and then by further improvement). The number of effective units in the data envelopment analysis (DEA) showed a decreasing, followed by an increasing, trend from seven in 2012 to eight in 2017.

Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Fujian, and Guangdong have always been the major production areas in China. Low ecoefficiency areas are mainly in the western region. The ecoefficiency of areas with inconsistent input and undesired output is low, as seen in Liaoning with respect

Table 3: Ecoefficiency values for 30 regions in China (2006–2017).

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Tianjin	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Hebei	0.57	0.55	0.56	0.54	0.49	0.41	0.43	0.47	0.46	0.45	0.45	0.43
Shanxi	0.38	0.34	0.35	0.35	0.30	0.29	0.27	0.26	0.26	0.27	0.27	0.24
Inner Mongolia	0.31	0.29	0.31	0.31	0.31	0.27	0.27	0.28	0.27	0.28	0.28	0.26
Liaoning	0.52	0.48	0.48	0.47	0.48	0.48	0.47	0.45	0.45	0.44	0.42	0.41
Jilin	0.38	0.36	0.36	0.39	0.40	0.40	0.39	0.40	0.40	0.40	0.40	0.40
Heilongjiang	1.00	0.46	0.46	0.45	0.47	0.44	0.45	0.41	0.41	0.41	0.41	0.42
Shanghai	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiangsu	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Zhejiang	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Anhui	0.50	0.49	0.48	0.45	0.44	0.44	0.48	0.46	0.46	0.47	0.46	0.45
Fujian	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Jiangxi	0.49	0.47	0.45	0.45	0.44	0.43	0.43	0.43	0.44	0.45	0.46	0.45
Shandong	1.00	0.58	0.58	0.57	0.57	0.56	0.60	0.57	0.60	0.62	0.63	0.65
Henan	0.57	0.51	0.50	0.49	0.47	0.47	0.46	0.45	0.46	0.46	0.45	0.43
Hubei	0.56	0.54	0.54	0.51	0.50	0.47	0.46	0.45	0.45	0.45	0.43	0.42
Hunan	0.46	0.46	0.48	0.50	0.44	0.46	0.45	0.47	0.47	0.47	0.43	0.45
Guangdong	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Guangxi	0.36	0.39	0.40	0.37	0.41	0.42	0.42	0.39	0.40	0.40	0.38	0.40
Hainan	1.00	1.00	1.00	1.00	1.00	1.00	0.51	0.57	1.00	1.00	1.00	1.00
Chongqing	0.49	0.44	0.43	0.42	0.41	0.41	0.41	0.42	0.42	0.43	0.44	0.45
Sichuan	0.50	0.50	0.49	0.47	0.45	0.45	0.49	0.47	0.48	0.48	0.48	0.48
Guizhou	0.28	0.26	0.27	0.27	0.26	0.27	0.25	0.24	0.25	0.25	0.25	0.26
Yunnan	1.00	0.44	0.38	0.37	0.36	0.35	0.33	0.34	0.34	0.35	0.36	0.35
Shaanxi	0.45	0.41	0.42	0.41	0.43	0.43	0.42	0.40	0.40	0.41	0.42	0.41
Gansu	0.28	0.28	0.27	0.27	0.26	0.25	0.24	0.24	0.25	0.24	0.23	0.24
Qinghai	0.30	0.29	0.29	0.30	0.29	0.29	0.27	0.27	0.27	0.28	0.27	0.28
Ningxia	0.13	0.13	0.15	0.12	0.12	0.13	0.12	0.12	0.12	0.12	0.12	0.11
Xinjiang	0.30	0.26	0.26	0.24	0.22	0.22	0.20	0.18	0.18	0.18	0.19	0.19

Data are calculated according to equation (7).

to urban water. Industrial SO_2 emissions and smoke (powder) dust emissions were higher than the national average in Liaoning, while the GDP of Ningxia and Xinjiang over the 12-year period was markedly different from the national average. These factors were responsible for the relatively low ecoefficiencies in these areas.

The analysis showed that GDP is not necessarily reflected in regional ecoefficiency. In 2015, Sichuan, Hubei, and Hunan had larger GDP values, but lower ecoefficiency, than Fujian; economically underdeveloped areas can still achieve ecological efficiency by rationally adjusting their industrial structure and optimizing output. For example, in 2006, the GDP of Yunnan was less than a fifth of that of Shandong, but its ecoefficiency was 60% higher. Thus, regional ecoefficiency is not dependent only on the economic output.

4.3. Coordinated Development. The TOPSIS algorithm was used to measure the level of intensity of urban land use and regional ecological development in various provinces of China from 2006 to 2017 (Table 4). Spatial and temporal aspects of coordinated development were analyzed. Based on K-means clustering and regional economic and social development data, the study area was divided into four categories: low coordination (0–0.3), moderate coordination (0.3–0.5), moderate-to-high coordination (0.5–0.7), and high coordination (0.7–1.0). Figure 1 shows the classifications for 30 provinces from 2006 to 2017.

The average coordination value between intensive land use and the ecological economy in China for the period 2006–2017 was 0.524, indicating considerable room for improvement. Most provinces had moderate or moderate-to-high coordination. The number of provinces with low and moderate coordination values showed an upward trend over the period 2006–2017, while the moderate-to-high coordination areas showed a fluctuating, but ultimately decreasing, trend.

Despite some volatility, there was significant overall improvement in the level of coordination, particularly after 2007 and 2012. Implementation of the Eleventh Five-Year Plan and Twelfth Five-Year Plan promoted rational allocation of production and coordinated overall development of the Chinese economy and society. From 2007 to 2011, economic development was rapid, environmental pollution control efforts were strengthened, and the degree of coordination was high. From 2012 to 2017, the rate of urban construction in China began to slow down; more attention was paid to ecological construction, and coordination showed an upward trend.

Areas with high coordination were mainly distributed within the economically developed coastal areas in the east. Areas with high-to-moderate and moderate

Table 4: Coordinated development values for 30 regions in China (2006–2017).

Province	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Beijing	0.89	0.80	0.74	0.71	0.88	0.93	0.88	0.88	0.89	0.92	0.91	0.94
Tianjin	0.76	0.66	0.74	0.72	0.71	0.76	0.83	0.84	0.85	0.86	0.89	0.86
Hebei	0.58	0.54	0.57	0.60	0.60	0.62	0.57	0.57	0.58	0.58	0.61	0.59
Shanxi	0.42	0.36	0.35	0.37	0.33	0.36	0.33	0.33	0.34	0.34	0.36	0.37
Inner Mongolia	0.28	0.29	0.31	0.36	0.31	0.31	0.32	0.32	0.33	0.34	0.32	0.32
Liaoning	0.66	0.60	0.67	0.71	0.70	0.71	0.55	0.60	0.61	0.63	0.65	0.65
Jilin	0.34	0.29	0.29	0.30	0.28	0.31	0.26	0.27	0.28	0.29	0.32	0.31
Heilongjiang	0.50	0.49	0.52	0.54	0.57	0.59	0.61	0.62	0.63	0.64	0.63	0.65
Shanghai	1.00	1.00	1.00	1.00	0.99	0.90	0.90	1.00	1.00	1.00	1.00	1.00
Jiangsu	0.78	0.70	0.83	0.83	0.89	0.89	0.86	0.86	0.88	0.90	0.94	0.95
Zhejiang	0.74	0.74	0.79	0.79	0.78	0.80	0.82	0.83	0.83	0.85	0.87	0.86
Anhui	0.34	0.42	0.47	0.45	0.48	0.50	0.48	0.48	0.49	0.50	0.52	0.52
Fujian	0.84	0.75	0.84	0.88	0.91	0.89	0.90	0.92	0.93	0.94	0.92	0.96
Jiangxi	0.52	0.46	0.43	0.49	0.53	0.55	0.51	0.54	0.54	0.56	0.57	0.56
Shandong	0.80	0.74	0.82	0.83	0.83	0.86	0.85	0.86	0.87	0.88	0.84	0.83
Henan	0.58	0.55	0.54	0.54	0.49	0.48	0.47	0.48	0.49	0.52	0.54	0.58
Hubei	0.49	0.49	0.57	0.51	0.59	0.57	0.53	0.55	0.56	0.57	0.58	0.62
Hunan	0.48	0.48	0.46	0.45	0.52	0.54	0.52	0.54	0.54	0.56	0.57	0.59
Guangdong	0.68	0.64	0.68	0.70	0.72	0.74	0.76	0.77	0.78	0.82	0.85	0.85
Guangxi	0.31	0.38	0.33	0.32	0.36	0.38	0.40	0.42	0.44	0.45	0.47	0.45
Hainan	0.60	0.60	0.68	0.71	0.73	0.79	0.51	0.60	0.63	0.73	0.75	0.76
Chongqing	0.42	0.37	0.44	0.48	0.47	0.52	0.46	0.47	0.49	0.52	0.53	0.54
Sichuan	0.47	0.55	0.53	0.53	0.56	0.55	0.53	0.55	0.56	0.57	0.59	0.60
Guizhou	0.42	0.25	0.32	0.28	0.21	0.27	0.24	0.25	0.27	0.33	0.36	0.39
Yunnan	0.70	0.39	0.37	0.35	0.36	0.35	0.37	0.38	0.38	0.40	0.42	0.43
Shaanxi	0.52	0.52	0.53	0.56	0.55	0.53	0.52	0.54	0.54	0.56	0.55	0.54
Gansu	0.23	0.17	0.13	0.14	0.15	0.14	0.13	0.14	0.15	0.16	0.17	0.17
Qinghai	0.26	0.31	0.25	0.25	0.25	0.31	0.35	0.36	0.37	0.38	0.39	0.39
Ningxia	0.00	0.00	0.05	0.06	0.13	0.14	0.06	0.08	0.09	0.10	0.15	0.16
Xinjiang	0.23	0.15	0.15	0.14	0.13	0.12	0.14	0.14	0.15	0.19	0.22	0.24
Average	0.53	0.49	0.51	0.52	0.53	0.55	0.52	0.54	0.55	0.57	0.58	0.59

Data are calculated according to Section 3.3.

Figure 1: Coordinated development value of 30 provinces in China.

coordination were mainly distributed in the central and northeastern regions. Low coordination regions were mainly in the west.

The coordination between intensive urban land use and the development of the ecological economy shows a significant regional variation in China. Coordination differs according to the level of economic development and regional development policies. With further regional economic integration, different regions must implement land regulations and environmental management policies to promote sustainable development of economic society.

5. Conclusions

We constructed a model based on the TOPSIS method to measure coordination between intensive urban land use and the ecological economy in China, for the period 2006–2017. We then analyzed spatial and temporal aspects of coordination across Chinese provinces. Our conclusions are as follows:

(1) Despite large regional differences in the intensity of urban land use, there was an overall upward trend. The intensity of urban land use was consistent with the degree of economic development. The intensity was the highest in the eastern region, possibly due to the rational allocation of production and efficient use of resources in this region. The western and northeastern regions had the least intense land use. Due to its rich resources and industrial history, the eastern region lags behind in resource utilization efficiency and industrial adjustment. The central region has benefitted from the transfer of industrial

activity from the eastern region, reflected in intensive land use.

(2) Ecoefficiency showed a downward trend over the study period at the regional level. In the eastern coastal areas, ecological efficiency did not accord with GDP. Rational allocation of production could improve regional ecological efficiency.

(3) The average coordination value (between intensive land use and the ecological economy) for the period 2006–2017 in China was ~0.524, indicating considerable room for improvement. The low and moderate coordination provinces accounted for about 46% of all provinces in all years of the study period, indicating that improving coordination between land use and economic development will be a difficult, but important, task. The degree of coordination is consistent with the intensity of urban land use; improvement in the latter could provide ecological benefits.

Based on these findings, the following conclusions can be drawn:

(1) Under resource and environmental constraints, an improper relationship between the development of land resources and ecological protection measures may weaken regional cooperation and hinder the implementation of policies promoting urban development. More attention should be paid to rational allocation of production at the regional level, mutually beneficial development policies, and land regulations that promote ecoefficiency. Regional environmental protection policies could not only benefit economic and social development but also resolve the tension between the former and ecological construction.

(2) Land resources should be rationally allocated at the policy level; the scale of urban development should be effectively controlled by improving natural resource taxation. Furthermore, environmental pollutants should be monitored more closely, and the economical, societal, and ecological needs should all be considered. Finally, enthusiasm for ecological protection should be fostered among all relevant stakeholders by establishing a mechanism for cross-regional ecological compensation.

Data Availability

The data, models, or code used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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