Comparative Analysis of the Factors Influencing Land Use Change for Emerging Industry and Traditional Industry: A Case Study of Shenzhen City, China

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Abstract: Analyzing the factors influencing emerging industry land use change is important for promoting industrial transformation and for upgrading and improving the level of intensive use of emerging industry land. In recent years, to solve the problem of land resource shortage and expansion space, Shenzhen has implemented a strategy of promoting urban development through technological innovation and has actively promoted the transformation of inefficient industrial land to emerging industry. This article introduces the development, land use types, and spatial distribution of Shenzhen’s emerging industries. Based on the logistic regression model, we analyze the differences between the factors influencing changes in land use for both emerging and traditional industry. The research results show that the distance from public roads, the distance from highways, the distance from railway freight stations, the proportion of secondary industry, and the proportion of tertiary industry are important explanatory variables for the two types of land use change. Traditional industrial land use is also affected by the land slope, the distance from ports, the population, and fixed asset investment. Emerging industry land use is also affected by the distance from the airport, the number of railway stations, the quality of the population, and innovation-driving forces. These results provide a reference for government to rationally plan emerging industry land and differentiated management of this, in order to fill the current research gap in the field of land use change, and to contribute to research revealing the mechanisms driving changes in emerging industrial land.

Keywords: emerging industry land; influencing factors; logistic regression model; land use change; intensive land use; Shenzhen

1. Introduction

Since reform and opening up, China has experienced constant rapid economic growth and industry has been an important driving force [1]. In 2019, the value of China’s industrial output reached RMB 39 trillion, accounting for 40% of its GDP [2]. With accelerated urbanization and industrialization processes, the amount of industrial land is growing rapidly. From 2009 to 2019, the area of industrial land increased by 33% from 8627 to 11,479 km<sup>2</sup> [3,4]. In addition, some industrial land is idle or is extensively used with low efficiency [5,6]. Therefore, determining how to promote the intensive use of industrial land has become the focus of attention [7,8]. As urban development enters the era of stocks, the issues of the withdrawal and transformation of low-efficiency industrial land have become increasingly important [9]. It is no longer possible to effectively match the development requirements of industrial upgrading through long-term, low or free price transfer of industrial land to attract investment [10]. It is necessary to implement a differentiated land...
management model based on the development of different industries [11]. Therefore, dividing industrial land into multiple types is conducive to promoting the effective coupling of industrial land supply and demand. It is also conducive simultaneously to promoting the further development of regional economies. However, few research cases have been published on the classification of industrial land.

Land use intensity was first introduced by Ricardo and other classical economists while conducting agricultural land research [12], which was later applied in the fields of urban economics, land economics, land use planning, etc. [13–15]. Developed countries began urban land use research early. Starting in the 1920s, the ecological school [16], regional economic school [17], social behavior school [18], and political economic school [19] emerged in succession, and each has provided important contributions to the theoretical research. Some scholars approached urban land use from the perspectives of natural space, economic space, social space, and political space and focused on revealing its dynamic change and processes [20–23]. Regarding the causes of urban land use change, some researchers considered land price, technological change, economic growth, and political and economic structures, and explored the dynamic mechanism of the evolution of urban land use change [24–27]. In the second half of the 20th century, to cope with urban sprawl, some scholars probed planning policies in depth, such as those related to growth management [28], smart growth [29], urban growth boundaries [30], and compact cities [31]. Research on the intensive use of urban land in China began in the 1990s. Research on land use has mainly focused on evaluation index systems [32], spatial layouts [33], and use efficiency [34]. At present, characterizing the factors that impact land use change is the core focus of research, and this study plays a key role in revealing the basic process, driving reasons, future change prediction, and related policy formulation [35]. In terms of methods and research objects, scholars have mostly used statistical analysis methods based on regression models to study the impact factors by statistically calculating the distributions of industrial land [36], rural residential land [37], and ecological land [38] in different element spaces. Some scholars have also analyzed the impact of the distribution of industrial land on urban growth based on regression models [39,40]. At the research-area scale, most scholars chose hotspot areas with active natural and human factors or ecologically fragile areas [41,42] to strengthen research through the selection of research objects and case comparisons. In the selection of influencing factors, most scholars have focused on natural, economic, and social factors. Current research shows that human activities and climate change are the main factors driving land use change [43,44].

Emerging industry land has been created to promote industrial transformation and upgrading, to increase the economic output of land, and to achieve industry–city integration. This is an adjustment applied by the government in response to industrial upgrading and urban development, which can solve the current mismatch between industrial development and land supply [45]. Therefore, research on land use change for emerging industry is of vital importance. In 2019, the Guidelines for the Implementation of Industrial Land Policy (2019 Edition) stated that more land use space should be released by changing the land use mode and by improving land use efficiency to ensure the development of new industries and new formats of business and to satisfy the demand for the construction of facilities to support people’s livelihoods [46]. In the industrial upgrading process, some industrial land has been used for research and development, design activities, offices, and businesses, thereby making the land (the spatial carrier) naturally assume a variety of forms. Some scholars have suggested that the introduction of the knowledge economy inevitably posed new challenges to traditional industry and that technological innovation has become an important factor in land use change in emerging industry [47]. However, the research has mostly remained at the theoretical level. The main reasons are as follows: (i) Emerging industry is wide in scope but does not have a clear definition and connotation at present. (ii) The transformation of traditional industry into emerging industry is complex and diverse, resulting in a blurred boundary. (iii) Emerging industry land has not
become an independent type among all present land types, so the data are hard to define and obtain.

In summary, the existing research mostly selected industrial land as a single object and did not distinguish between traditional industry land and emerging industry land, and there is a lack of empirical analyses of emerging industry land. Therefore, the factors influencing land use change in emerging industry and traditional industry revealed by these studies are likely to be biased. In view of this, we selected Shenzhen as an example and the emerging industry land and traditional industry land as the research objects, and explored the differences in the factors influencing land use change between emerging industry and traditional industry through empirical research. The findings are expected to provide a scientific basis for the rational planning of emerging industry land and the differentiated management of industrial land, to fill the current research gap in the field of land use change, and to contribute to existing research cases revealing the mechanisms driving changes in emerging industry land.

2. Materials and Methods

2.1. Study Area

2.1.1. Overview of Shenzhen City

Shenzhen (22°27′–22°52′ N, 113°46′–114°37′ E) is located in Southern Guangdong Province, adjacent to Hong Kong, with a total area of 1996 km² (Figure 1). Since the establishment of the special economic zone, Shenzhen has experienced rapid urbanization which is now unsustainable in four aspects: land, resources, population, and environment [48,49]. In recent years, the Shenzhen municipal government has issued a series of development plans and supporting policies to promote industrial transformation and upgrading and to actively promote the transformation of inefficient industrial land into emerging industry land to solve the problems of land resources and developing space shortages [50]. As a key player in China’s reform and opening up, this area is a representative city for the development of emerging industries in China. It is characterized by a high urban economic level, rapid development of emerging industries, and high availability of relevant spatial data. Therefore, it is an ideal object for research into new industrial land.

![Figure 1. Location of Shenzhen in China and the districts in Shenzhen.](image)

2.1.2. Types of Emerging Industry Land in Shenzhen

Land is the carrier of emerging industries [51]. Compared with factory buildings on industrial land, emerging industry land is more diverse in its spatial form. The emerging industry land in the city is mainly used as follows: (i) High-tech industrial parks, which have been established for the development of high technology industry, including the Dashahe innovation corridor in Nanshan District, Che Kung Temple Industrial Zone in...
Futian District, Huawei Tech City in Longgang District, the Xixiang agglomeration in Baoan District, and the high-tech industry park in Guangming District. (ii) Creative industry parks, which have been established for the development of creative industries and a creative economy and have been mainly upgraded from inefficient industrial zones and urban villages. (iii) Business incubators, which are specific places established to provide enterprises with technical training and financial support for their growth, including the business incubator bases in Nanshan and Longgang Districts. (iv) Corporate headquarters, which are formed when high-end sectors are separated from the internal organizational structure. The corporate headquarters in Shenzhen, where decision making, marketing, and research and development are conducted, include Huawei, Tencent, Lenovo, Baidu, and more than 60 high-technology companies. (v) Makerspaces, where innovation is the core concept. These innovative workshops provide products and services for users through creative designs, including the Chaihuo (“firewood”) makerspace, the DIY community, the Kaiyuan makerspace workshop, youth innovative and entrepreneurial dream workshops. (vi) Industrial buildings, apart from functioning as places to make products, which are mainly transformed or updated from industrial plants, can also serve as offices for business or financial services or as places for trade shows.

2.1.3. Spatial Distribution of Emerging Industry Land in Shenzhen

Emerging industry land in Shenzhen covers an area of 1821 hm\(^2\), accounting for 6.65% of the total area of the city’s industrial land, with wide spatial distribution differences (Table 1): (i) Emerging industry is mainly concentrated in the Nanshan District, with an area of 623 hm\(^2\), accounting for 34% of the total area of the city’s new industry land. This has occurred because there are high-tech zones, university towns, headquarters, and other innovation and talent resources in Nanshan District. (ii) Emerging industry, to a large degree, is also distributed in Longgang District, with an area of 458 hm\(^2\) accounting for 25% of the total area of the city’s new industry land. This has occurred because Longgang District is an important industrial production base. In the urban development process, some industrial land in Longgang District was the first to be upgraded to emerging industry land. (iii) Emerging industry is also widely distributed in Baoan and Futian Districts, with an area of 381 hm\(^2\), accounting for 20% of the total area of the city’s new industry land. This has occurred because finance and industry are well-developed in these two districts. (iv) Emerging industry is also present in smaller amounts across Luohu, Longhua, Guangming, and Pingshan Districts, with an area of 344 hm\(^2\), accounting for the 19% of the total area of the city’s new industry land. This has occurred because the creative environment and industrial development in these four districts is not as strong as in the above four districts. (v) There is a small amount of emerging industry land in the Yantian and Dapeng Districts, with an area of 15 hm\(^2\), which is less than 1% of the total area of the city’s new industry land. This has occurred mainly because these two districts are focused on developing coastal tourism and ecological protection.
Table 1. Types and distribution of emerging industry land in Shenzhen.

| District | Area (hm²) | Proportion of the Total Area of the City (%) | High-Tech Industrial Parks | Creative INDUSTRIAL Parks | Enterprise Incubators | Corporate Headquarters | Makerspaces | Industrial Buildings |
|----------|------------|---------------------------------------------|---------------------------|--------------------------|----------------------|-----------------------|------------|---------------------|
| Luohu    | 69         | 3.79%                                       | 6                         | 5                        | 2                    | 2                     | -          | -                   |
| Futian   | 212        | 11.64%                                      | 7                         | 10                       | 4                    | 12                    | -          | 2                   |
| Nanshan  | 623        | 34.21%                                      | 14                        | 10                       | 34                   | 35                    | 5          | 2                   |
| Yantian  | 9          | 0.49%                                       | -                         | 1                        | 1                    | -                     | -          | -                   |
| Baan     | 169        | 9.28%                                       | 26                        | 9                        | 10                   | 3                     | 2          | -                   |
| Longgang | 458        | 25.15%                                      | 17                        | 14                       | 8                    | 5                     | 1          | -                   |
| Guangming| 115        | 6.32%                                       | 2                         | 2                        | 2                    | 1                     | -          | -                   |
| Pingshan | 42         | 2.31%                                       | 2                         | 2                        | 2                    | 1                     | -          | -                   |
| Longhua  | 118        | 6.48%                                       | 3                         | 8                        | 2                    | 2                     | -          | -                   |
| Dapeng   | 6          | 0.33%                                       | 2                         | 1                        | 2                    | -                     | -          | -                   |
| Total    | 1821       | 100.00%                                     | 79                        | 61                       | 67                   | -                     | -          | -                   |

2.2. Data Sources

The land use data required in this study was obtained from surveys of land use change over the years in Shenzhen city. The DEM data were obtained from the Shenzhen Municipal Bureau of Planning and Natural Resources. The demographic, social, and economic data were from the Shenzhen Statistical Yearbook and the national economic and social development statistics bulletin. The emerging industry data were obtained from the Shenzhen municipal government website and an external investigation.

2.3. Methods

The logistic regression model is a nonlinear classification and statistical method in which the response variables are two- or multiple-category data, and the independent variables can be qualitative or quantitative [52]. The model was developed by Verhult, a biomathematician, in 1838 [53], and it has been successfully applied in many areas, such as changes in wildlife habitat [54], forest fire prediction [55], and forest land degradation [56]. The model is as follows:

\[
\ln \left( \frac{P}{1-P} \right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n
\]  

(1)

where \(P\) is the probability of land use change; \(\alpha\) is a constant; \(\beta_1, \beta_2, \beta_3, \ldots, \beta_n\) are the partial regression coefficients of logistic regression; and \(X_1, X_2, X_3, \ldots, X_n\) are the explanatory variables.

The probability of land use change is a nonlinear function composed of explanatory variables. The formula is as follows:

\[
p = \frac{\exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}{1 + \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}
\]

(2)

The occurrence ratio is used to explain the regression coefficient of each variable, calculated by the index of the parameter evaluations:

\[
\text{odds}(p) = \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)
\]

(3)

The predictive ability of the logistic regression model is assessed by obtaining the maximum likelihood estimation, which includes the Wald statistics of the regression coefficient estimation, the significance level of the regression coefficient estimation, and the index Exp (B) of the parameter estimates. Unlike other regression methods, the \(R^2\) cannot be used to test the effect of the regression in logistic regression, so the receiver operating
characteristic (ROC) method proposed by Pontius is used to test the logistic regression. Generally, when the ROC value is greater than 0.7, a model has a good interpreting ability. The closer the ROC area is to 1, the better the model [57].

In this study, according to the principles of comprehensiveness, representativeness, relevance, and difference [58], combined with the actual situation in Shenzhen, five major categories—natural conditions, traffic locations, population, economic development, and innovation drive—were analyzed. These categories included 18 factors. The influencing factors are able to have a relatively stable effect on the change in land use in a short period. Even if there is a change in the effect, the change is immediate rather than gradual [59]. (i) Emerging industry land was introduced in Shenzhen in 2009, so the influencing factors were chosen from the land use change data from 2009 to 2019. (ii) Industrial land policies have been relatively stable in Shenzhen city since 2000, so the influencing factors were chosen from the land use change data from 2000 to 2019. The dependent variables and independent variables are listed in Table 2.

Table 2. Establishment of the dependent variables and independent variables dataset.

| Variable                      | Factor                                         | Type                   | Units         |
|-------------------------------|------------------------------------------------|------------------------|---------------|
| Dependent                     | land use change in emerging industry (2009–2019) | two-category classification | 0–1           |
|                               | land use change in traditional industry (2000–2019) | two-category classification | 0–1           |
| natural conditions            | elevation                                      | continuous             | m             |
|                               | land slope                                      | multi-category classification | 1–3           |
| traffic locations             | distance from highways                          | continuous             | km            |
|                               | distance from public roads                      | continuous             | km            |
|                               | distance from airports                          | continuous             | km            |
|                               | distance from ports                             | continuous             | km            |
|                               | distance from railway freight stations          | continuous             | km            |
| population                    | change in population size                       | continuous             | 10^4 persons  |
|                               | change in population quality                    | continuous             | %             |
| economic development          | GDP change                                      | continuous             | 10^8 yuan     |
|                               | change in proportion of secondary industry      | continuous             | %             |
|                               | change in proportion of tertiary industry       | continuous             | %             |
|                               | change in fixed assets investment               | continuous             | 10^8 yuan     |
| innovation drive              | change in number of regional patent applications | continuous             | number        |
|                               | change in number of regional science and research institutions (universities and science and research institutions) | continuous             | number        |
|                               | change in number of regional primary and middle schools | continuous             | number        |
|                               | change in number of regional libraries, exhibition halls, and museums | continuous             | number        |

Next, we established a GIS database of various factors, with each factor as one layer. Then, the data were converted to raster format and the resolution was set to 200 × 200 m². Figure 2 and Appendix A Figure A1 show the grid maps of the factors of the dependent variables and independent variables, respectively.
3. Results and Analysis

3.1. Results for Emerging Industry Land

Twelve of the eighteen selected factors were found to have an effect on the land use change of emerging industry in Shenzhen, including the distance from public roads; the distance from highways; the distance from airports; the distance from railway freight stations; the number of railway stations; the quality of the population; the proportion of secondary industry; the proportion of tertiary industry; the number of regional patent applications; the number of regional science and research institutions; the number of regional primary and middle schools; and the number libraries, exhibition halls, and museums.

From the explanatory variables entered into the model (Table 3), the following were concluded: (i) Regarding the distance from public roads, the distance from airports, the quality of the population, the proportion of the secondary industry, the proportion of tertiary industry, the number of regional science and research institutions, and the number of regional patent applications, if their relative weights are greater than 20, these factors contribute considerably to the land use changes of emerging industry. The ranking of the contributions of these influencing factors shows that traffic locations, economic development, and innovation drive are the main forces driving the creation of emerging industry land. (ii) Regarding the distance from railway freight stations, the number of railway stations, the proportion of secondary industry, the proportion of tertiary industry, the number of regional patent applications, and the number of regional science and research institutions, if the Exp(B) values are greater than one, the probability of emerging industry land use change increases when the values of these six factors change.

| Variable                                                        | Wald $x^2$ Statistics | Significance Level | Exp (B) |
|-----------------------------------------------------------------|-----------------------|--------------------|---------|
| Distance from public roads                                      | 6.15                  | *                  | 0.84    |
| Distance from highways                                          | 173.76                | *                  | 0.29    |
| Distance from airports                                          | 25.40                 | *                  | 0.66    |
| Distance from railway freight stations                          | 5.72                  | *                  | 1.22    |
| Number of railway stations                                      | 19.57                 | *                  | 1.43    |
| Quality of population                                           | 24.39                 | *                  | 0.79    |
| Proportion of secondary industry                                | 53.92                 | *                  | 1.84    |
| Proportion of tertiary industry                                 | 66.57                 | *                  | 10.80   |
| Number of regional patent applications                          | 50.80                 | *                  | 2.04    |
| Number of regional science and research institutions (universities and science and research institutions) | 45.02                 | *                  | 1.83    |
Table 3. Cont.

| Variable                                      | Wald $x^2$ Statistics | Significance Level | Exp (B) |
|-----------------------------------------------|-----------------------|--------------------|---------|
| Number of regional primary and middle schools | 4.41                  | *                  | 0.04    |
| Number of regional libraries, exhibition halls, and museums | 16.84                | *                  | 0.39    |
| Constants                                     | 46.02                 | *                  | 0.00    |
| ROC                                           |                       |                    | 0.83    |

3.2. Results for Industrial Land

Nine of the eighteen selected factors have an effect on industrial land use change in Shenzhen, including the land slope, the distance from public roads, the distance from highways, the distance from ports, the distance from railway freight stations, the size of population, the proportion of secondary industry, the proportion of tertiary industry, and the fixed asset investment.

From the explanatory variables entered into the model (Table 4), the following were concluded: (i) Regarding the distance from public roads, the distance from ports, the size of the population, the proportion of secondary industry, and the fixed asset investments, if their relative weights are greater than 30, the contributions of these factors to emerging industry land use changes are relatively large. The ranking of the contributions of these influencing factors shows that traffic locations and economic development are the main forces driving the emergence of industrial land in Shenzhen. (ii) Regarding the land slope, the distance from ports, the distance from railway freight stations, the size of the population, the proportion of secondary industry, the proportion of tertiary industry, and the fixed asset investments, if their Exp (B) values are greater than one, the probability of industrial land use change increases when the values of these seven factors change.

Table 4. Model estimation results of the influencing factors of industrial land use in Shenzhen.

| Variable                                      | Wald $x^2$ Statistics | Significant Level | Exp (B) |
|-----------------------------------------------|-----------------------|--------------------|---------|
| Land slope                                     | 28.70                 | *                  | 1.22    |
| Distance from highways                        | 13.60                 | *                  | 0.86    |
| Distance from public roads                    | 538.65                | *                  | 0.30    |
| Distance from railway freight stations        | 78.55                 | *                  | 1.76    |
| Size of population                            | 36.50                 | *                  | 1.24    |
| Proportion of secondary industry              | 38.81                 | *                  | 1.32    |
| Proportion of tertiary industry                | 14.24                 | *                  | 1.77    |
| Fixed asset investments                       | 30.76                 | *                  | 1.14    |
| Constant                                      | 53.26                 | *                  | 0.00    |
| ROC                                           |                       |                    | 0.81    |

3.3. Comparative Analysis

When a logistic regression model was used to simulate the factors influencing land use change in emerging industry and traditional industry, the accuracy rate of prediction was higher than 70%, and the ROC test values reached 0.8263 and 0.8146, respectively (Figure 3). The degree of fit of the model is good, which shows that the logistic regression equation has a very strong explanatory ability.

As shown by the explanatory variables entered into the model, the factors influencing land use change in emerging industry and traditional industry in Shenzhen are different, but the distance from public roads, the distance from highways, the distance from railway freight
stations, the proportion of secondary industry, and the proportion of tertiary industry are important explanatory variables in both types of land use change (Table 5). This is perhaps because, in the urban development process, regions with stronger economies and better traffic locations can attract more investment and have a higher demand for land, which lead to an increase in the chances of agricultural land being converted into emerging industry land or industrial land, especially in highly urbanized areas, such as Futian and Nanshan Districts.

(i) Natural conditions. The two explanatory variables, elevation and slope, were not included in the regression model of emerging industry land use, which shows that natural conditions have minimal effects on the land use change of emerging industry, perhaps because emerging industry land is mainly from newly transferred land, innovative industrial parks, and cultural and creative parks, which are similar in their natural conditions. The land slope is included in the regression model of industrial land use, probably because flat terrain is more likely to be chosen when selecting industrial land sites. The terrain in Shenzhen is mostly low hilly land with gentle slopes, and there are no obvious changes in altitude; therefore, areas with low slopes are more likely to be chosen for industrial land.

(ii) Traffic locations. The two explanatory variables, the number of railway stations and the distance from airports, were included in the regression model of emerging industry land use rather than industrial land, probably because the regional locations and aviation economy produce large differences in the exports of emerging industries. Since part of emerging industry land has been transformed from traditional industry land, more mature industry development and more convenient transportation increase the likelihood that emerging industry regions are formed. The distance from ports was included in the regression model of industrial land use, indicating that foreign capital and technology have major influences on the change in industrial land use and that ports play an important role.

(iii) Population. The size of the population was included the land use regression model of traditional industry rather than that of emerging industry. The quality of the population is exactly the opposite, mainly because during the industrialization process in Shenzhen, most of the industry has been labor-intensive and thus has relied strongly on labor availability. With advances in technology, abundance of capital, and shortage of land resources, some industrial enterprises have been updated from the original “three types of processing plus compensation trades” [60]. Before 2008, there was no emerging industry land in Shenzhen. This land did not appear until 2009 in Nanshan District, where science and technology have reached very high levels, and in Longgang District, where there is a relatively large industrial area. Innovative industry strongly depends on talent, so population quality has become an explanatory variable of emerging industry land use.

(iv) Economic development. The two explanatory variables, proportion of secondary industry and proportion of tertiary industry, were included in both the land use regression models of emerging industry and traditional industry, mainly because the development of secondary and tertiary industries has motivated land use change. Industrial development increases the chance of agricultural land being converted into emerging industry land or industrial land. From the differences between the two, industrial land is more affected by fixed asset investments, mainly because the change in the amount of fixed asset investments directly affects the area of industrial land, thus affecting industrial land change. Emerging industry lies between secondary industry and tertiary industry, and it is more likely to appear in the regions where tertiary industry is well-developed.

(v) Innovation drive. Four influencing factors, the number of regional patent applications; the number of regional universities and science and research institutions; the number of regional primary and middle schools; and the number of regional libraries, exhibition halls, and museums, were all included in the land use regression model of emerging industry rather than that of traditional industry, which shows that innovation drive has
a marked impact on the land use change of emerging industry but a relatively small impact on industrial land use change. As shown in the distribution of the emerging industry land in Shenzhen, emerging industry land is close to science and research institutions and libraries, and the educational facilities around it are relatively mature. These factors work together to attract emerging industry. In contrast, industrial land is more dependent on roads, rail transportation, and other municipal facilities.

![Figure 3](image)

*Figure 3. ROC test values of (a) emerging industry land and (b) industrial land.*

| Variable          | Factor                                                | Influence on the Land Use Change in Emerging Industry | Influence on the Land Use Change in Traditional Industry |
|-------------------|-------------------------------------------------------|-----------------------------------------------------|---------------------------------------------------------|
| natural conditions| elevation                                             | -                                                   | -                                                       |
|                   | land slope                                            | -                                                   | √                                                       |
|                   | distance from highways                                | √                                                   | √                                                       |
|                   | distance from public roads                            | √                                                   | √                                                       |
| traffic locations  | distance from airports                                | √                                                   | -                                                       |
|                   | distance from ports                                   | -                                                   | √                                                       |
|                   | distance from railway freight stations                | √                                                   | √                                                       |
|                   | distance from railway stations                        | √                                                   | -                                                       |
| population        | size of population                                    | -                                                   | √                                                       |
|                   | quality of population                                 | √                                                   | -                                                       |
| economic development| proportion of secondary industry                      | √                                                   | √                                                       |
|                   | proportion of tertiary industry                        | √                                                   | √                                                       |
|                   | fixed asset investments                               | -                                                   | √                                                       |
| innovation drive  | number of regional patent applications                 | √                                                   | -                                                       |
|                   | number of regional science and research institutions (universities and science and research institutions) | √ | - |
|                   | number of regional primary and middle schools         | √                                                   | -                                                       |
|                   | number of libraries, exhibition halls, and museums    | √                                                   | -                                                       |
4. Discussion

In previous studies, scholars have mostly used regression models to calculate the distribution of urban construction land, agricultural land, and ecological land and conducted analyses of natural, economic, and social influencing factors [61–64]. Among these, the research on the change in industrial land did not distinguish between traditional industry land and emerging industry land. Additionally, empirical analysis of emerging industry land is lacking, and the results of the analysis of factors influencing industrial land use changes revealed by these articles deviate somewhat [65,66]. Compared with these, our research provides the following innovations: (i) In the cases where current policy does not clarify the specific type of emerging industry land, we combined the land use practices in Shenzhen to summarize and refine the spatial form of emerging industry land, which provides a reference for the subsequent formulation of classification standards. (ii) We used a logistic regression model to quantitatively analyze the factors that cause spatial changes in emerging industry land and traditional industry land; thus, the research conclusions are more suitable for the development and planning of emerging industry land. (iii) We innovatively considered the factors driving innovation in land use changes, used remote sensing and geographic information system technology to process source data and influencing factor data on the basis of comprehensive consideration of multiscale factors, and used the administrative area as a unit to match the physical space and land; therefore, the quantitative results are more accurate.

Because land use change is a complex process, this study has the following limitations: (i) Due to the limitations of data acquisition, population and economic factors were quantified with the street as the unit. If more accurate data are acquired, the results can be interpreted more accurately [67]. (ii) Different stages of development will influence the results of the logistic regression model differently [68]. Since the history of emerging industry is short, no comparative analysis is possible amongst its different stages. (iii) Planning policies will affect land use change [69]. It is difficult to quantify the two factors in space, so the focus of future research will be to select quantifiable indexes. (iv) Classical regression analysis is usually based on independent samples, but spatial correlation can affect the accuracy of the finding [70], so the relevant theory and practice remain to be studied further.

Although the spatial model established in this study revealed some of the factors driving changes in industrial land, it still cannot predict when the changes will occur. Therefore, to improve the prediction probability of land use change, we recommend the establishment of a dynamic model that considers the driving forces in subsequent research. These driving forces should include dynamic factors such as the formulation of new policies and changes in the price of industrial land. As such, the driving force representing the reason for the possibility of change can be revealed by the spatial model.

5. Conclusions

Since 2009, emerging industry has developed rapidly in Shenzhen, which is playing an increasingly important role in social and economic development. Emerging industry land in Shenzhen has assumed a variety of spatial forms, including high-tech industrial parks, creative industrial parks, business incubators, corporate headquarters, makerspaces, and industrial buildings. Regarding spatial distribution, the emerging industry land in Shenzhen mainly occurs in Nanshan District, given its advantages in terms of innovative resources and talent, and in Longgang District, which has advantages in manufacturing.

We used a logistic regression model to explore the differences between the factors influencing land use change for emerging industry land and those for traditional industry. The research results showed that five factors, the distance from public roads, the distance from highways, the distance from railway freight stations, the proportion of secondary industry, and the proportion of tertiary industry, are important explanatory variables of land use change in both emerging and traditional industries. In addition, industrial land use is affected by the land slope, the distance from ports, the size of the population, and
fixed asset investments, while emerging industry land use is affected by the distance from airports, the number of railway stations, the quality of the population, and the factors driving innovation.

Based on a logistic regression model, we identified the most important factors influencing the changes in emerging industry land and traditional industry land and analyzed the degree of influence of each factor on these changes. In terms of practice, the findings provide a decision-making reference for Shenzhen government departments for the reasonable planning of emerging industry land and the differentiated management of industry land to encourage them to scientifically guide land use structure while developing the economy. As such, they can organize the most effective production activities in the best areas and achieve the best land resource use efficiency. In terms of theory, our findings help to fill the current research gap in the field of land use change and contributes to the research revealing the mechanisms driving changes in emerging industry land.

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**Appendix A**

![Figure A1. Cont.](image-url)
(c) Distance from highways

(d) Distance from public roads

(e) Distance from airports

(f) Distance from ports

(g) Distance from railway freight stations

(h) Number of railway stations

(i) Population size

(j) Population quality

Figure A1. Cont.
(k) GDP (l) Proportion of secondary industry

(m) Proportion of tertiary industry  (n) Fixed asset investments

(o) Number of regional patent applications  (p) Number of regional science and research institutions (universities and science and research institutions)

(q) Number of regional primary and middle schools  (r) Number of libraries, exhibition halls, and museums

Figure A1. Grid maps of the independent variables.
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