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Research Article

Physical and Socioeconomic Driving Forces of Land-Use and Land-Cover Changes: A Case Study of Wuhan City, China

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To investigate precise nexus between land-use and land-cover changes (LUCC) and driving factors for rational urban management, we used remotely sensed images to map land use and land cover (LULC) from 1990 to 2010 for four time periods using Wuhan city, China, as a case study. Partial least squares (PLS) method was applied to analyze the relationships between LUCC and the driving factors, mainly focusing on three types of LULC, that is, arable land, built-up area, and water area. The results were as follows: (1) during the past two decades, the land-use pattern in Wuhan city showed dramatic change. Arable land is made up of the largest part of the total area. The increased built-up land came mainly from the conversion of arable land for the purpose of economic development. (2) Based on the Variable Importance in Projection (VIP), the joint effects of socioeconomic and physical factors on LUCC were dominant, though annual temperature, especially annual precipitation, proved to be less significant to LUCC. Population, tertiary industry proportion, and gross output value of agriculture were the most significant factors for three major types of LULC. This study could help us better understand the driving mechanism of urban LUCC and important implications for urban management.

1. Introduction

Land-use and land-cover changes (LUCC) increasingly have been regarded as a primary source of global environmental change such as emission of greenhouse gases, global climate change, loss of biodiversity, and loss of soil resources [1–3]. However, the causes of LUCC are complex and change over time and from region to region [4]. In the early 1990s, keeping in view the diverse reasons and causes of land-use change emphasizes the importance of interdisciplinary research to address the issue of land-use change with a particular focus on the human dimensions [5]. LUCC have been led by a set of socioeconomic driving forces and conditioned by different natural endowments [6] that determine the trajectories of landscape development [7]. Understanding the driving mechanisms of LUCC caused by a variety of driving forces is one of the major goals of global change research in recent decades [8–10].

To understand the human and biophysical processes of LUCC, many researchers focus on the various forces driving LUCC, including socioeconomic [11], demographic [12], political [13], technological [14], biophysical [15], and industrial structure [16], to provide effective support for developing urban land planning and management regulations. To comprehensively analyze the driving factor's effects and mitigate the negative impacts of land-use change, Shu et al. (2014) [17] investigated the effects of various factors, including natural ecoenvironment factors, land control policies, accessibility factors, and neighborhood factors, on urban land expansion during various periods in different regions. Chen et al. (2014) [18] selected industrial structure, GDP, transportation, and policy as the driving factors to study the impacts on urban land expansion and sustainable urban development in Shenzhen and Dongguan. In addition, an integration of biophysical and human factors was applied in the explanation of

LUCC dynamics of Mediterranean Europe due to its particular climatic and physical conditions [15]. Obviously, the outstanding characteristics of the studied cases, such as economy, culture, climate, and policy, often were considered as the important driving forces in the explanation of LUCC dynamics. However, though many researches on land-use change have been conducted, climate factors were seldom available on driving analysis of LUCC.

Various research methods were employed to explore the nexus between LUCC and their driving forces. Multivariate regression was used to model how the major forces drive the physical expansion of urban land cover at the global level [19]. Li et al. (2013) [20] applied binary logistic regression to investigate the effects of the selected driving variables on the probability of urban expansion. Analytic hierarchy process (AHP), as a subjective method, provided rigorous quantitative measures to understand the interactive process of urban growth and factors [21]. System dynamics (SD) was combined with CLUE-S model to reflect the complexity of the land-use system [22], regarded as a macrolevel, "top-down" implementation process. However, few attempts have been made to investigate precise nexus between LUCC and driving factors. Partial least squares (PLS) method, as a major regression technique for multivariate data, may handle highly correlated noise-corrupted data sets by explicitly assuming the dependency between variables and estimating the underlying structures [23]. It could effectively reflect the significant PLS components using the cross validation technique [24]. In the paper, PLS was used to accurately reflect the nexus between LUCC and driving factors, meanwhile determining the significant components of the selected driving factors.

In the paper, our main objectives were to address the processes of land-use dynamics in Wuhan city and its integrated driving forces through combining satellite-based efforts at mapping land use and land cover (LULC) and physical, socioeconomic data. Based on RS images in 1990, 1995, 2000, 2005, and 2010, we analyzed the variant change of each LULC type during 4 periods (1990–1995, 1995–2000, 2000–2005, and 2005–2010). Thirteen variables of physical and socioeconomic factors were selected as the potential driving factors of LUCC. Partial least squares (PLS) method is applied to select the important driving factors and analyze the relationships between LUCC and the factors triggering each land-use change type, mainly focusing on three major types of LUCC, that is, arable land, built-up land, and water area. Finally, we suggested some possible management measures that are crucial for future sustainable utilization and management of its existing land resources, for example, managing urban growth and protecting cultivated land.

2. Study Area

Wuhan city, as a central hinterland megalopolis of China, is situated in the east of Jianghan plain and covers over 8494.41 km^2 (113°41′–115°05′ E, 29°58′–31°22′ N). Terrain is dominated by flat areas with a surface elevation ranging from 0 to 100 m, and the slope is less than 10°, making up 95.78% of the total. The low hills, which have an elevation between 200 and 400 m and a slope varying from 10 to 25°, constitute 3.89% of its total area, while the mountainous area (elevation 400~800 m; slope >25°) accounts for only 0.33% (Figure 1). The Yangtze River and its largest tributary Han River meet here, which divides Wuhan into three parts, Hankou, Hanyang, and Wuchang, commonly known as "the three towns of Wuhan." The area has the subtropical humid monsoon climate. Its climate feature is obvious, characterized by abundant rainfall, summer heat, and winter cold, with an annual temperature of approximately 15.8–17.5°C and mean annual precipitation of 1150–1450 mm. A huge water network was formed with the Yangtze River as the backbone and supplemented by quantities of lakes or ponds. Therefore, Wuhan city has a reputation of "city of hundred lakes." The water area accounts for 25.6% of the city area.

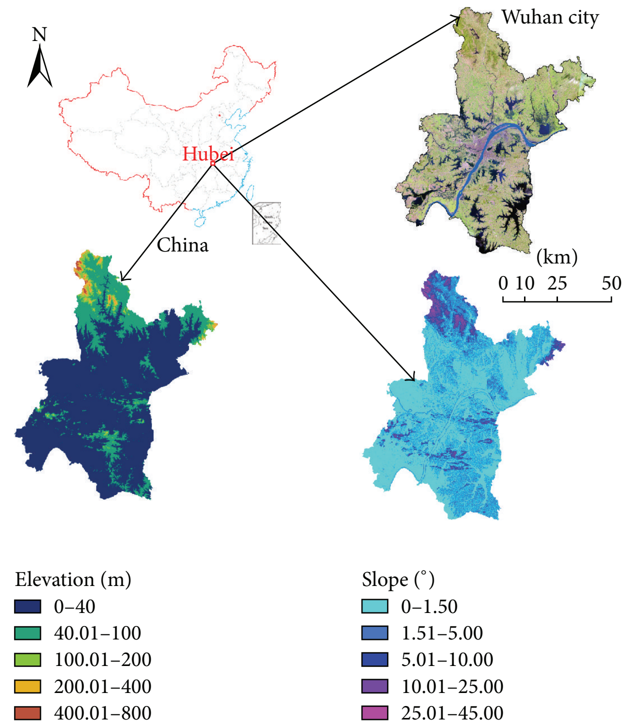


Figure 1: Location of the study area.

After entering the twenty-first century, Wuhan's economic growth speed has accelerated. In 2010, per capita GDP in Wuhan amounted to 66,520 Yuan RMB [25], which was much higher than the average GDP per capita (22,936 Yuan RMB) in China. The urbanization level increased from 56.2% in 1990 to 64.7% in 2010. Wuhan's population has been increasing by an annual rate of 1.20% since 1978. With a total population of about 8.36 million, the population density in Wuhan city was up to 984 persons/km^2 in 2010, which was much higher than the average population density (141 persons/km^2) of China at the same period [25, 26]. 32.3% of total population was engaged in farming.

However, with the population growth and economic development, LULC in Wuhan has changed dramatically as evidenced by the rapid increase of built-up land at the expense of occupying massive high quality arable land in the urban fringe areas. Moreover, to gain more construction space, some land exploitation activities, such as deforestation and the filling of lakes for the sake of construction space, occurred. In addition, climate factors have caused certain effects on LUCC [27]. Therefore, it is very necessary to identify the important factors triggering LUCC, in order to mitigate the contradiction between human and land.

3. Methodology and Data

3.1. Remotely Sensed Imagery Preprocessing, Interpretation, and Land-Use Detection. The analysis of LUCC in Wuhan city was based on five LULC maps, which were derived from historical Landsat MSS/TM/ETM+ images (path/row, 122/39, 123/38, 123/39). To obtain the information of land-use classification, the paper used Landsat MSS images for 1990 and 1995, Landsat TM images for 2000 and 2005, and Landsat ETM+ images for 2010. The interpretation scheme adopted was the combination of supervised classification and visual modification. All the procedures were processed using ENVI 5.0 and ArcGIS Desktop 10.1 software. The detailed interpretation process was elaborated in our previous published paper [28]. Landscape of the study area was divided into six major land-use types: pasture, arable land, built-up land, forest, water area (including rivers, ponds, reservoirs, and aquaculture waters), and unused land. Moreover, in order to solve the insufficiency of sample data and increase modeling accuracy, linear interpolation method was used to generate the time-series data of land use from the year 1990 to 2010. Thus, we could use the time-series data of six major land-use types to explore the driving forces contributing to land-use change in Wuhan city. In addition, the six major land-use types, that is, pasture, arable land, built-up land, forest, water area, and unused land, were labeled as y_1, y_2, y_3, y_4, y_5, and y_6, respectively. A flow chart describing the detection procedure of LUCC was shown in Figure 2.

3.2. Data of Driving Factors. LUCC is a result of the complex interactions between human activity and physical factors. According to the related studies [11, 13, 15, 17], four types of driving factors of LUCC have been generally identified: physical factors, socioeconomic factors, neighborhood factors, and land-use policies [20]. Although similar driving factors could be found in the related literatures, the magnitude of the effects which contributed to landscape change differed [29]. In this paper, we selected thirteen variables representing physical, economic, and social factors. Because the paper mainly focused on a longitudinal time-series effect of the driving forces on land-use change, neighborhood factors as spatial data were considered in the study. Meanwhile, we did not include land-use policies because of the lack of long-term data on these aspects.

Physical factors are the fundamental determinants of the extent of land-use change. Climate conditions, such as precipitation and temperature, affect the potential extent of LULC by restricting the water supply. Therefore, the annual precipitation (x_1) and the annual temperature (x_2) were included as the climatic factors for studying the driving factors of LUCC in Wuhan city. These climatic data were collected from China Meteorological Data Sharing Service System (http://www.escience.gov.cn/metdata/page/index.html). Socioeconomic factors include time-series data on population (x_3), urbanization rate (x_4), regional gross domestic product (GDP) (x_5), tertiary industry proportion (x_6), gross industrial output value (x_7), gross output value of agriculture (x_8), total retail sales of consumer goods (x_9), gross imports and exports (x_{10}), per capita disposable income of households (x_{11}), turnover volume of passenger traffic (x_{12}), and turnover volume of freight traffic (x_{13}). These historical data were extracted from the statistical yearbook of Wuhan [25] and China statistical yearbook [26]. These factors reflect the dynamics of population and urbanization, economic and industrial structure, social investment, technological progress, and external traffic conditions, which may have potential influences on LULC change in Wuhan city. In addition, to achieve comparability in price across the studied period, all the factors related to price were converted to the constant price of 1990 based on the corresponding index of each factor and the general consumer price index.

3.3. Partial Least Squares Regression. PLS is a well-known multivariate statistical technique for the analysis of high dimensional data, developed by Wold (1975, 1984) [30, 31]. The function of PLS included multiple linear regression analysis, canonical correlation analysis, and principal component analysis. It originated in the social sciences and became popular in many fields including first chemometrics [31], sensory evaluation [32], and statistics [33] and ecology [34]. The increasing popularity of PLS is partly due to more powerful functions of dealing with multicollinearity that existed in the dataset, especially in some case of fewer observations relative to the number of variables, compared to conventional statistical method [35].

PLS aims at investigating relationships between the predictor (i.e., independent or explanatory) and the response (i.e., dependent or explained) variables. The dataset of independent variables, the matrix $X_{m\times n}$, consists of m variables (columns) and n objects (rows). And the dataset of dependent variables constitutes a response vector $Y_{n\times 1}$. In this paper, the independent variables were the thirteen driving factors, and dependent variables were different land-use types. The basic idea of PLS is to identify two sets of components or factors (also called latent variables), that is, t_i and u_i, extracted from the independent variables X and dependent variables Y, respectively, which can maximize the explained variance in original X-values and Y-values. There are two important plots used to evaluate the applicability of the PLS method: t_1/u_1 scatter graph and the t_1/t_2 oval graph. If there is linear relationship between t_1 and u_1, indicating X significantly correlated to Y, it is reasonable to construct PLS linear model between X and Y [33]. If t_1/t_2 of the sample data is all included in the oval plot, these sample data are homogeneous and can be accepted perfectly.

It is critical to determine the optimal number of latent variables when building the PLS model. In the paper, Leave-One-Out Cross Validation (LOOCV) was used to determine the number of latent variables (principal components). The

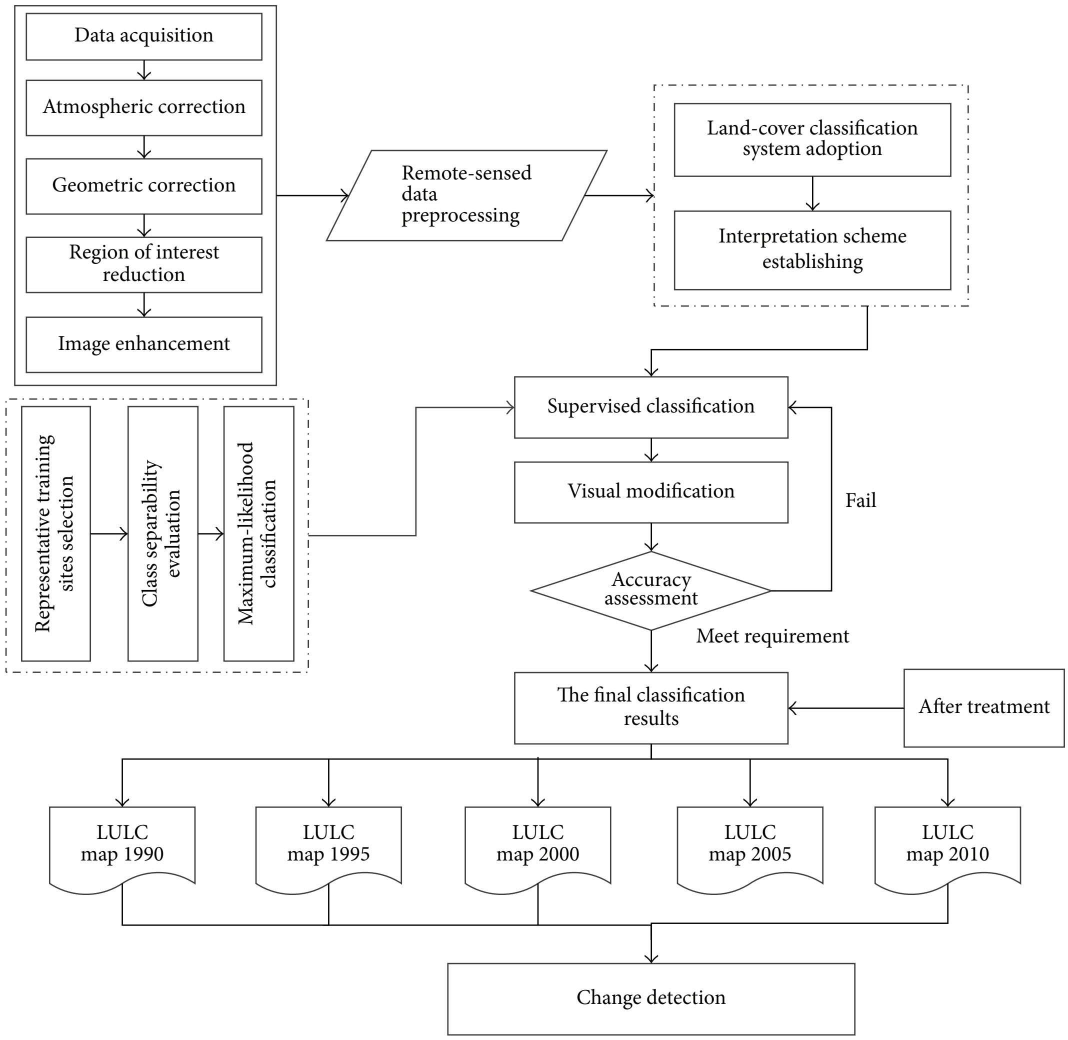


Figure 2: Flow chart of detection procedure of LULC changes.

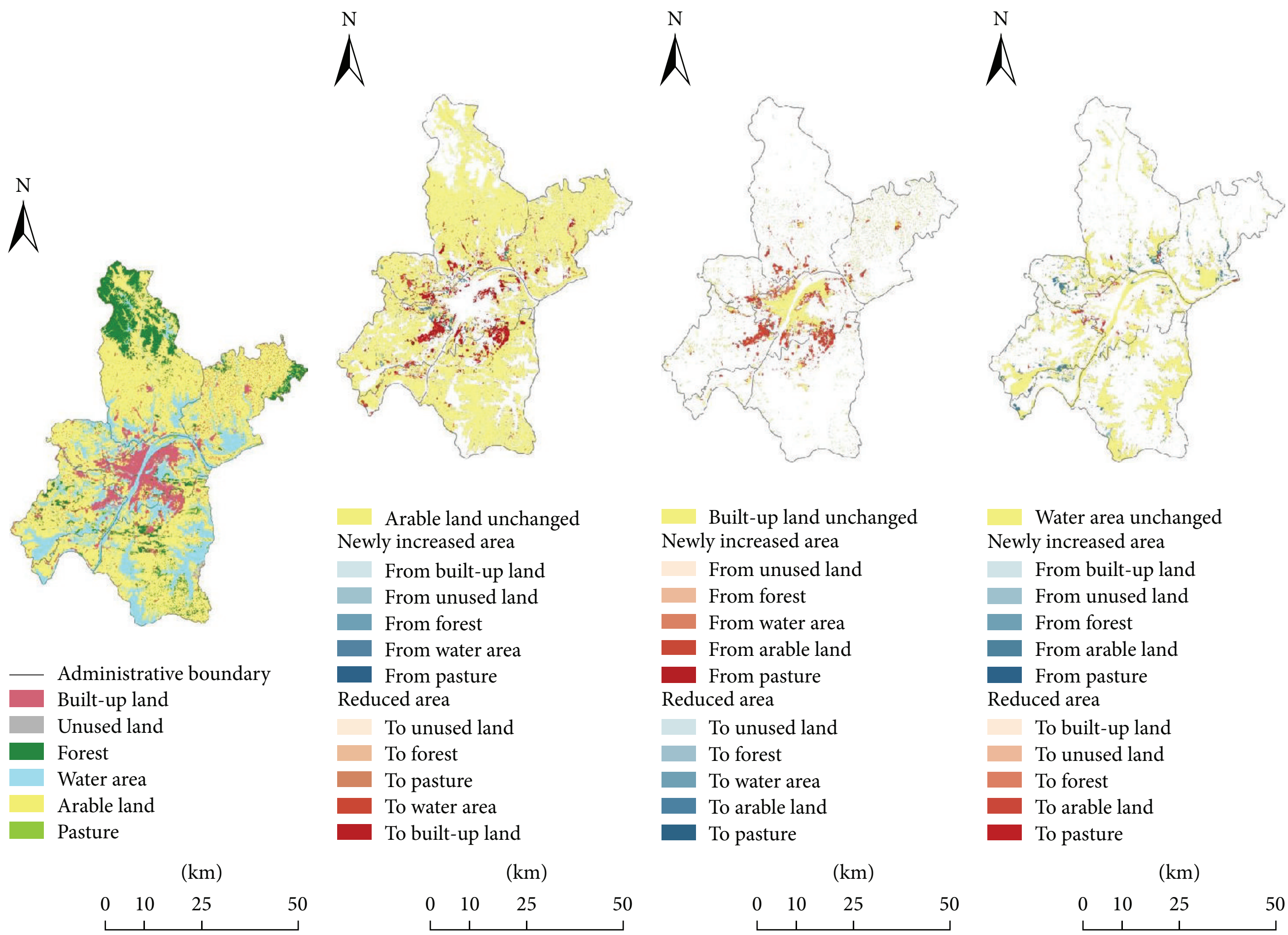
LOOCV systematically omits one plot at a time and performs n-estimates of the parameters using $n-1$ plots. This procedure was repeated for all plots [36]. The LOOCV statistical parameters including ${R_h}^2$, ${Q_h}^2$, ${R_{\mathrm{cm}}}^2$, and ${Q_{\mathrm{cm}}}^2$ were calculated to determine the confidence in the model performance. ${R_h}^2$ was the percent of variation of the independent variables explained by the model, which could measure how well the model fits the data (h represents the number of principal components). ${Q_h}^2$ was the percent of variation of the dependent variables predicted by the model according to cross validation, which indicated how well the model predicts new data. ${R_{\mathrm{cm}}}^2$ and ${Q_{\mathrm{cm}}}^2$ were the cumulative R^2 and Q^2 over all the selected PLS components. When ${R_{\mathrm{cm}}}^2$ and ${Q_{\mathrm{cm}}}^2$ are greater than 0.8, the model was considered to exhibit good predictive ability.

In the PLS method, the Variable Importance in Projection (VIP) was employed to determine the relative importance of driving factors with respect to the response variables [35]. Terms with large VIP values are the most relevant for explaining the dependent variables. The jth predictor's VIP score to the response variable can be written as

$$\mathrm{VIP}_j = \sqrt{\frac{N}{R_d\left(Y; t_1, t_2, \ldots, t_m\right)} \sum_{h=1}^{m} R_d\left(Y; t_h\right) w_{hj}^2}, \tag{1}$$

where N is the dimension of input variables; m is the number of latent variables; $R_d(Y; t_1, t_2, \ldots, t_m)$ represents the explanatory capacity of components for dependent variables; w_{hj} denotes the loading weight vectors for each component and represents the importance of the variable j for component h; $j = 1, 2, 3, \ldots, N$, $h = 1, 2, 3, \ldots, m$.

For VIP scores that are larger than a threshold, that is, $\mathrm{VIP}_j \geq S_{\mathrm{VIP}}$, the predictors should be selected as input variables. In general, the greater-than-one rule is used as a criterion for variable selection. In the paper, VIP scores mainly are used to discern the different importance of the driving factors, especially between physical factors and socioeconomic



(a) LULC map in 2010 (b) Arable land from 1990 to 2010 (c) Built-up land from 1990 to 2010 (d) Water area from 1990 to 2010

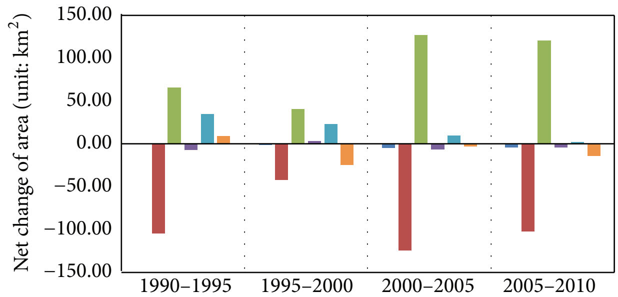
FIGURE 3: LULC map and the spatial change of main LULC types in Wuhan city from 1990 to 2010.

factors in the land-use change. SIMCA-P 11.5 Software was performed to implement the PLS procedure.

4. Results and Analysis

4.1. Characteristics of LULC Change in Wuhan City. Figure 3 showed the change tendency of main LULC types in Wuhan city from 1990 to 2010. As observed, arable land is made up of the largest part of the total area and mainly distributed in the plain area, crisscrossed by a network of rivers and lakes. In contrast, the distribution of the built-up land was more centralized and mainly situated in the central district of Wuhan, but there were also some rural settlements scattered evenly in the whole study area. During the period 1990~2010, built-up land showed a noticeable trend of outward expansion along the Yangtze River and Han River, occupying a large amount of arable land and some water body. The water area is also an important component of Wuhan and provides important ecological functions. The central and southern parts have more lakes and rivers gathering there when compared with the northern areas. As shown in Figure 3, from 1990 to 2010, some waters in the central area were converted to pasture and built-up land, while the newly emerging built-up land was mainly converted from pasture and arable land. The forest of Wuhan was mainly located in the northwestern and northeastern hilly areas, and some forest reserve or urban forest parks in the south. The land-use pattern of the forest was relatively stable throughout the study period. The pasture and unused land are distributed in the remote mountains and waterfront areas. Due to the restrains from topography and geomorphology, drainage and irrigation, and ecological protection, the exploitation potential of the unused land was quite limited.

Figure 4 showed the net change of LULC types during four periods (1990–1995, 1995–2000, 2000–2005, and 2005–2010) in Wuhan city. As observed, LULC has changed greatly, especially during the latter two periods. From 1990 to 1995, arable land and the forest decreased by 103.98 and 6.45 km^2, respectively. In contrast, built-up land, water area, and unused land increased by 65.90, 35.62, and 8.31 km^2 in the same period. These trends of changes slowed down in the period from 1995 to 2000. By the end of 2000, built-up land and water area expanded by 41.24 and 24.01 km^2. Most of the newly developed areas were from arable land and the unused



	1990–1995	1995–2000	2000–2005	2005–2010
Pasture	0.60	−1.05	−4.18	−4.61
Arable land	−103.98	−42.46	−123.91	−101.49
Built-up land	65.90	41.24	127.79	121.23
Forest	−6.45	3.06	−7.01	−3.87
Water area	35.62	24.01	10.07	1.94
Unused land	8.31	−24.80	−2.76	−13.20

Figure 4: Net change of each LULC type in Wuhan city (unit: km^2).

land, and their areas decreased by 42.46 and 24.80 km^2, respectively. The period from 2000 to 2005 witnessed the most significant changes in arable land and built-up land. The former shrunk by 123.91 km^2, while the latter increased by 127.79 km^2, and the areas of the other four LULC types were relatively stable within this period. The increased built-up land came mainly from the conversion of arable land for the purpose of development. The trends of changes continued in the last period from 2005 to 2010. Therefore, we could conclude that arable land, built-up land, and water area were three main LULC types. Therefore, in Section 4.4, we mainly analyzed the relationships between the three main LULC types and driving factors to reveal the driving mechanism of LUCC in Wuhan city.

4.2. Parameters of Partial Least Square Regression and Its Accuracy. As shown in the t_1/u_1 scatter graph (Figure 5(a)), the t_1/u_1 relationship of the sample data is nearly linear; thus, PLS regression model is suitable for the study of the problem of this paper. From the t_1/t_2 oval graph (Figure 5(b)), it was clear that all the sample data collected from 1990 to 2010 were acceptable except the sample point from the year 2010 because this point was not included in the oval. In order to obtain better model fitting performance, the regression model was rebuilt after eliminating the outlier.

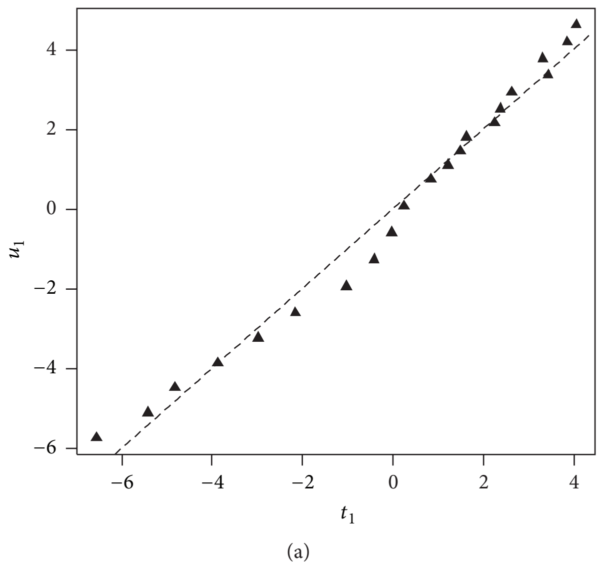
As shown in Table 1, two indicators, that is, R_h^2 and Q_h^2, were used to determine the number of principal components. When three principal components were extracted from variables, the values of $Q_h^2 < 0$ (for all LULC types), which could not meet the decision criterion of $Q_h^2 \geqslant 0.0975$. In addition, it is generally held that the regression effect is ideal, when R_{cm}^2 and Q_{cm}^2 are all larger than 0.8 [37]. Thus, two principal components were the best for the total and most of the LULC types. Table 1 shows 94.9% variation of the dependent variables can be explained by the model, and the accumulated cross validation reached 93.5%, suggesting that the regression results are effective.

4.3. Variable Importance Analysis. For in-depth analysis of variable's interpretative ability, the importance of a variable was given by the Variable Importance in Projection (VIP). It is generally held that the independent variable plays a very important role when the VIP value is larger than 1.0 and relatively important when the VIP value is larger than 0.5 and smaller than 1.0, whereas the VIP value smaller than 0.5 indicates weak interpretative ability [38]. As shown in the VIP histogram (Figure 6), it was clear that the annual precipitation (x_1) did not have much influence on the dynamics change in land system over 20 years from 1990 to 2010, because the VIP value was only 0.284. On the contrary, gross output value of agriculture (x_8) had the greatest interpretative ability, followed by population (x_3) and urbanization rate (x_4), per capita disposable income of households (x_{11}), regional gross domestic product (GDP) (x_5), total retail sales of consumer goods (x_9), turnover volume of passenger traffic (x_{12}), tertiary industry proportion (x_6), gross industrial output value (x_7), gross imports and exports (x_{10}), and turnover volume of freight traffic (x_{13}), which proved to be the very important factors in explaining the changes that occurred in Wuhan, because their VIP values were larger than or equal to 1.0. The VIP value of annual temperature (x_2) was 0.714, which indicated that annual temperature was relatively less significant compared with these economic factors. Here, we obtained the terms with VIP values of independent variables in total land system, which could provide basics for driving forces of main LULC types in Section 4.4.

With regard to physical factors, especially for climatic factors, existing studies have provided enormous evidence of climatic factors influencing LULC change around the world [39]. For example, changing in temperature or rainfall

Table 1: Values of parameters under Leave-One-Out Cross Validation regression.

LULC types	h	R_h^2	R_{cum}^2	Q_h^2	Q_{cum}^2
Total	1	0.897	0.897	0.886	0.886
	2	0.052	0.949	0.429	0.935
	3	0.005	0.953	−0.055	0.931
Pasture	1	0.947	0.947	0.942	0.942
	2	0.020	0.967	0.257	0.957
	3	0.000	0.967	−0.110	0.953
Arable land	1	0.973	0.973	0.967	0.967
	2	0.015	0.988	0.469	0.983
	3	0.002	0.990	−0.059	0.982
Built-up land	1	0.990	0.990	0.989	0.989
	2	0.002	0.992	−0.021	0.989
	3	0.001	0.993	0.009	0.989
Forest	1	0.906	0.906	0.896	0.896
	2	0.001	0.907	−0.128	0.885
	3	0.001	0.908	−0.118	0.874
Water area	1	0.713	0.713	0.667	0.667
	2	0.234	0.947	0.772	0.924
	3	0.010	0.957	−0.090	0.917
Unused land	1	0.852	0.852	0.855	0.855
	2	0.038	0.891	0.201	0.884
	3	0.014	0.905	0.026	0.887



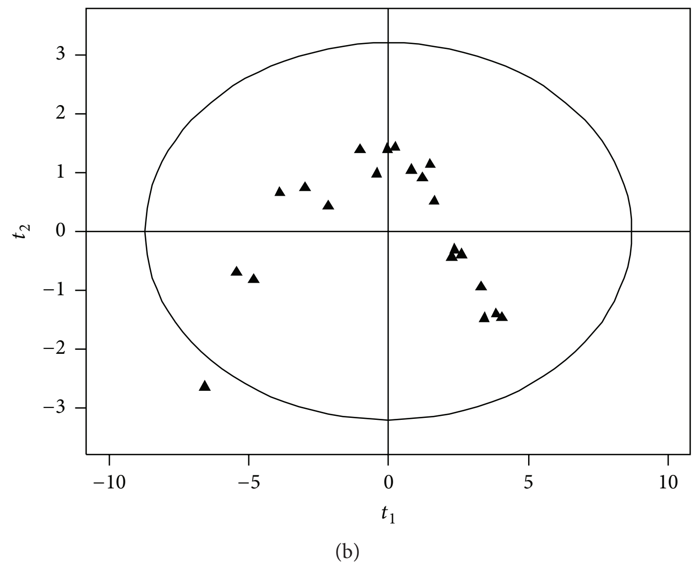


Figure 5: (a) t_1/u_1 scatter graph. (b) t_1/t_2 oval graph.

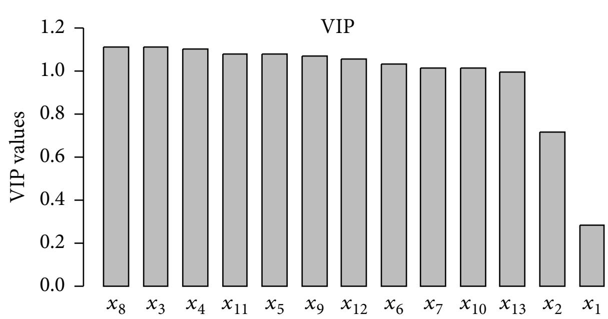


Figure 6: The VIP histogram of each variable.

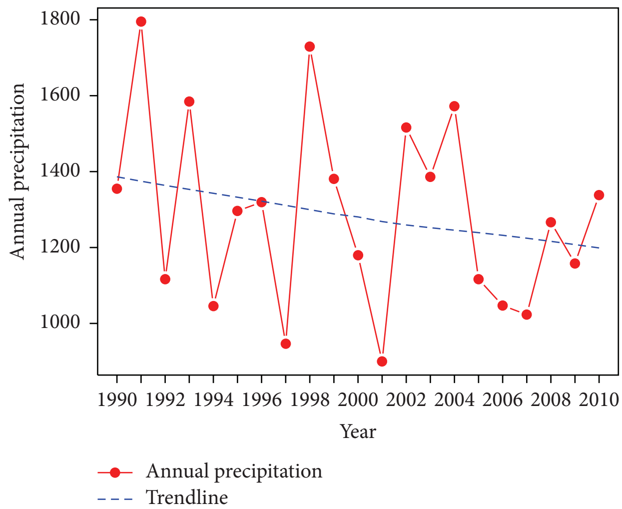
patterns might impact crop yield, farm profitability, regional productivity costs, and the number of people at risk of hunger [40]. Over the past two decades in Wuhan city, compared with the fluctuation trends of the annual precipitation (Figure 7(a)), the annual temperature continually rose in increasing trend (Figure 7(b)). Though the effect of LUCC on regional and global climate change has been well documented [41], in turn the temperature changes have reduced the regeneration ability of forests [42], furtherly affecting the LUCC. Meanwhile, decreasing rainfall can lead to the need for irrigation, which would increase the land for irrigation facilities. Therefore, the integrated factors, including physical factors, that is, temperature, and several socioeconomic factors, cooperatively shaped LULC changes. An elaborate analysis was launched illustrating the relationship of these variables with three main LULC types in Section 4.4.

4.4. Relationship between Different Land Types and Driving Factors

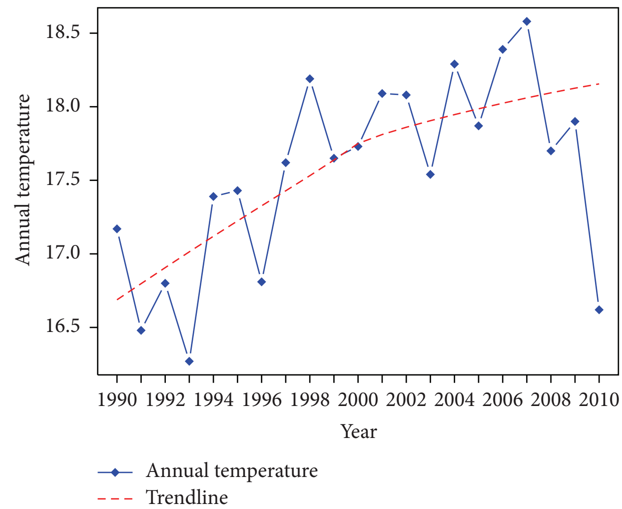
4.4.1. Arable Land Types and Driving Factors. To reveal the direction and strength of the impact of each independent variable on arable land, we used the PLS method to establish the regression equation as follows. It is worth mentioning that thirteen variables were considered to establish model, in order to not only be compared with the results based on VIP values but also discern different contributions of physical and socioeconomic factors to LUCC:

$$\begin{aligned} y_1 = {} & 0.030x_1 - 0.106x_2 - 0.117x_3 - 0.108x_4 \\ & - 0.087x_5 - 0.141x_6 - 0.066x_7 - 0.117x_8 \\ & - 0.086x_9 - 0.059x_{10} - 0.088x_{11} - 0.075x_{12} \\ & - 0.046x_{13} \quad \left(R^2 = 0.988\right). \end{aligned} \tag{2}$$

The equation showed the importance of every independent variable when explaining the dynamics of arable land from 1990 to 2010. $R^2 = 0.988$ indicated that thirteen factors interpreted 98.8% variation information of arable land and it suggested that the regression result was effective. From the signs of coefficients ((2), Figure 8), it could be known that the annual precipitation positively influenced the variation of arable land, while the annual temperature and the other eleven socioeconomic factors negatively did. Specifically, the influences of tertiary industry proportion, population, and gross output value of agriculture on arable land were the most obvious, and the coefficients were negative. The related results demonstrated that the area of arable land decreased along with the growth of tertiary industry proportion and population [43]. In Wuhan city, the share of the tertiary industry boomed from 25.0% to 51.4% during 1978–2010 [25]. Apparently, the adjustment of industrial structure in Wuhan was a very significant factor of arable land change and it played an important role in reducing the quantity of arable land. Besides, the increase of urban population and the improvement of people's living standards had facilitated the prosperousness of the real estate industry, which led to the conversion of arable land into constructing settlements as well as



(a)



(b)

Figure 7: (a) The graphs of annual precipitation. (b) The graphs of annual temperature.

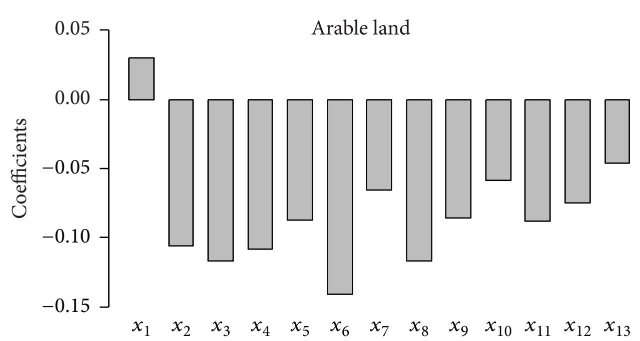


Figure 8: The coefficients of arable land.

providing various services for entertainment. Gross output value of agriculture was also negatively correlated with the change of arable land. The shares of farming, forestry, animal husbandry, and fishery in the gross output value of agriculture were 61.3%, 0.9%, 24.6%, and 13.2%, respectively, in 1990. However, they were 53.8%, 0.7%, 26.3%, and 18.7%, respectively, in 2010 [25]. The variation in the proportion illustrated the direction of agricultural structure adjustment in Wuhan, which greatly affected the LULC of Wuhan city. From the analysis of LULC patterns from 1990 to 2010, we could detect that a large proportion of arable land withdrew from crop cultivation for other purposes such as fishponds, orchards, or economic forest, which consisted in generating higher income through these production activities. In addition, the annual temperature posed negative effect on arable land in Wuhan city, which indicated the area of arable land slowly decreased along with local climate warming although their correlation was not significant. The annual precipitation was the only one positively correlated with arable land in Wuhan city, which indicated that the area of arable land had increase tendency along with the growth of the annual precipitation, although their correlation was not significant.

4.4.2. Built-Up Land Types and Driving Factors. The regression equation between the variables and built-up land was as follows:

$$\begin{aligned} y_2 = {} & -0.027x_1 + 0.068x_2 + 0.104x_3 + 0.101x_4 \\ & + 0.093x_5 + 0.101x_6 + 0.081x_7 + 0.104x_8 \\ & + 0.092x_9 + 0.078x_{10} + 0.094x_{11} + 0.087x_{12} \\ & + 0.072x_{13} \quad \left(R^2 = 0.992\right). \end{aligned} \tag{3}$$

As shown in Figure 9 and (3), the signs of coefficients were completely opposite to that of arable land. Except for the annual precipitation which negatively influenced the variation of built-up land, the other twelve factors positively did. $R^2 = 0.992$ indicated that the thirteen variables could interpret 98.8% variation information of built-up land. Furthermore, most of the socioeconomic factors contributed evenly to the change of built-up land. Population, gross output value of agriculture, urbanization rate, and tertiary industry proportion had the highest explanatory ability compared with the other factors considered in this paper. The area of built-up land would increase 0.104%, 0.104%, 0.101%, and 0.101%, when these four factors increase by 1%, respectively. The second group of factors followed were per capita disposable income of households, GDP, and total retail sales of consumer goods and they would lead to the increase of built-up land by 0.094%, 0.093%, and 0.092%, when they increase by 1%. These three factors had some similarities because they both reflected the performance of economic development and the improvement of people's life. As known, increasing economic activities and economic output led to increasing demand for built-up land. With the robust economic growth, local governments had the ability to expand public finances for development purposes, including generous investments in urban regeneration, key infrastructures, universities and schools, medical treatment facilities, and recreational parks,

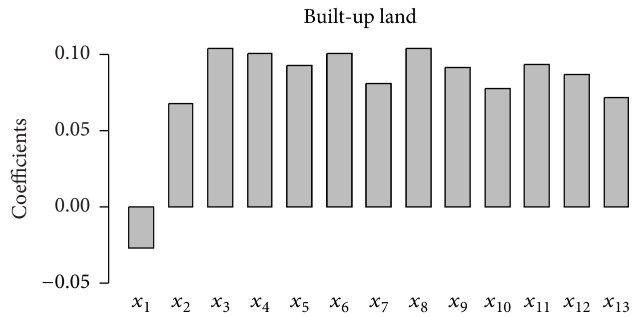


Figure 9: The coefficients of built-up land.

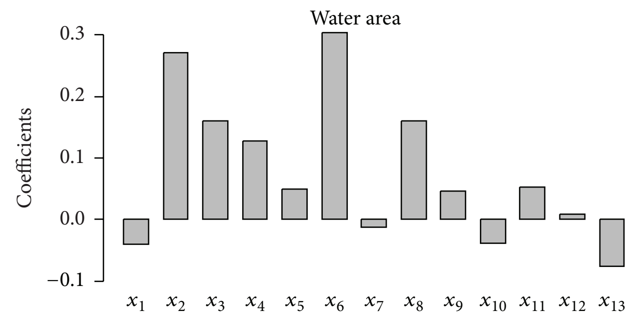


Figure 10: The coefficients of water area.

therefore resulting in rapid expansion of built-up land [44]. Meanwhile, the increase of the disposable income of households stimulated the demand for residential areas and facilities to improve their quality of life. Therefore, both government and residents contributed to the increase of built-up land. A 1% change in turnover volumes of passenger and freight traffic, respectively, induced 0.087% and 0.072% change in built-up land. Though the measure of traffic condition had relative effect on LULC, the construction of railway and highway programs directly led to the conversion from farmland to construction land. In contrast, annual precipitation negatively influenced the variation of built-up land, because the increase of precipitation could facilitate the regeneration ability of forests [27]. For temperature, it had positive feedback on the change of built-up land. Temperature will increase with the increase of urbanized and unexploited lands, while it will decrease with the increase of woodland, grassland, and farmland [27].

4.4.3. Water Area and Driving Factors. The regression equation between the independent variables and water area was as follows:

$$\begin{aligned} y_3 = {} & -0.040x_1 + 0.271x_2 + 0.161x_3 + 0.127x_4 \\ & + 0.050x_5 + 0.304x_6 - 0.013x_7 + 0.161x_8 \\ & + 0.047x_9 - 0.038x_{10} + 0.053x_{11} + 0.009x_{12} \\ & - 0.076x_{13} \quad \left(R^2 = 0.947\right). \end{aligned} \tag{4}$$

The relationship between these independent variables and water area was more complex than arable land and built-up land. Primarily, $R^2 = 0.947$ indicated that the thirteen variables could interpret 94.7% variation information of water area. From the signs of coefficients ((4), Figure 10), it could be known that the annual precipitation, gross industrial output value, gross imports and exports, and turnover volume of freight traffic posed rarely negative influence on the variation of water area, while the other nine factors positively did. Tertiary industry proportion proved to be the most significant factor in driving the change of not only arable land and built-up land but also water area. Moreover, it was noteworthy that the annual temperature had the second highest explanatory ability to the dynamics of water area, while it was not a significant factor in shaping arable land and built-up land changes. 1% change of the annual temperature would lead to 0.271% change of water area, greater than that of arable land and built-up land by 0.106% and 0.068%. This result showed that climate warming would have major impacts on water resources, which mainly contributed to the hydrologic cycle, precipitation, evaporation patterns, the magnitude and timing of runoff, and the intensity and frequency of floods and droughts, thus affecting seasonal availability of water supply [45]. However, the magnitude of annual temperature on the variation of water area still was limited compared with the joint effects of socioeconomic factors. With regard to the influences of population and urbanization, a largely urbanized and populated city was bound to push up the higher demand for water resources in Wuhan, reflecting in the amounts of water not only for surviving but also for offering ecological function and recreational function.

5. Conclusions

In the paper, we investigated the processes of land-use dynamics and the effects of physical and socioeconomic driving forces on LUCC in Wuhan city, Hubei province, China, through combining RS and PLS. The results indicate that the land-use pattern in Wuhan city showed dramatic change, with different net increase or decrease change speeds. Built-up land increased 356.16 km^2, and water area also enlarged 71.64 km^2 during the period 1990–2010. And the largest reducing magnitude for arable land reached 371.83 km^2. The increased built-up land came mainly from the conversion of arable land for the purpose of economic development. Based on VIP values, the joint effects of socioeconomic and physical factors on LUCC were dominant in the land system, though annual temperature, especially annual precipitation, proved to be less significant to LUCC. Population, tertiary industry proportion, and gross output value of agriculture were the most significant factors for three major types of LUCC. 1% change of the annual temperature would lead to 0.271% change of water area.

The study revealed a strong influence of integrated driving forces on LULC at regional scale. In the paper, PLS was applied with the Variable Importance in Projection as an appropriate technique contributing to eliminating the codependency among the variables, which has a better prospect than the traditional multiple linear regressions in this regard. However, the PLS methodology also has certain limitations that should be made clear. The interaction relationships between the driving forces and land-use changes are dynamics and nonlinear. As PLS is a method of linear modeling, the regression coefficient cannot fully capture the nonlinear relationship between driving forces and LULC change. Hence, to explore the detailed information of dynamic process of land-use change in complex land systems, a hybrid PLS regression and nonlinear models, such as back propagation neural network (BPNN), can be constructed to accommodate possible nonlinearity between the driving forces and LULC. This represents the future research efforts in deriving better dynamic models of LULC.

Competing Interests

The authors declare that they have no competing interests.

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