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Research Article

Prediction of the Impact of Land Usage Changes on Water Pollution in Public Space Planning with Machine Learning

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In urban public space planning, changes in land use, structure, and construction impact the urban environment to a certain degree. Land usage changes the urban surface water environment by impacting it through numerous ways. This paper studies about prediction of land use changes on surface water pollution in public space planning. This paper analyzes the characteristics of land use changes in public space planning from the quantitative characteristics of land use types, land use structure characteristics, and land usage degree in different years. The protection of natural resources is important, and water is one of the most important natural resources consumed by human beings. The environmental changes impacting these natural resources are to be studied to preserve the natural resources. The prediction of over-consumption of natural resources using soft computing techniques can certainly provide a solution for appropriate decision making. The prediction of relationship between land use changes and surface water pollution is required. In order to achieve this, the regression analysis on land use changes of different spatial scales with four surface water pollution indicators in the dry and wet seasons is performed to obtain the regression of each water pollution indicator. According to the determination coefficient, the determination coefficient of the model uses the comprehensive pollution index method to predict the impact of land use changes on surface water pollution. The experimental results show that the prediction accuracy of the proposed method is high and it is helpful in studying the impact of land use change on surface water pollution. It can help in decision making on consumption of natural resources to preserve the natural resources for next generations.

1. Introduction

There are some parameters in the urban public space planning which impact urban environment to a certain degree including change in land usage, structure of land, and construction on land [1]. The changes in land usage may change the urban water environment with respect to ecosystem and flow of energy in water systems [2]. This is the motivation behind the study of this paper which analyses the impact of land usage on the surface water pollution in public space planning. The land is the base for human survival and development [3]. Human beings are constantly changing the surrounding environment by utilizing and transforming land resources [4]. The impact on the environment is mainly manifested in the impact on land use changes. The land use is the direct and significant manifestation of human activities affecting the hydrological system [5]. The change of land use is the external manifestation of the process of land use activities. It is a dynamic change process in which natural and social human land usage is involved for the development of the infrastructure [6]. In recent decades, with the rapid growth of the world's population and the rapid development of science and technology, the intensity of land usage has been increased [7]. The extent of land use has reached or even exceeded the land's ecological carrying capacity, which leads to prominent surface water pollution. It can be considered as a severe threat to human survival and development [8].

In [8], the authors studied the impact of land use changes on the surface runoff. The megacity agglomeration is used as the research subject and the long-term hydrological impact assessment model is used to predict the outcomes of land usage. The data are taken from 2010 to 2015 which include land use data, soil data, and daily rainfall data. Over many years, the effects of different land use/cover patterns on the average surface runoff have been simulated and estimations are presented for decision making of future projects. In [9], the authors studied the impact of land use changes in the main urban area of Kunming on surface runoff using the daily rainfall and land usage data of five meteorological stations in the main urban area of Kunming from 1995 to 2014. The deterministic model simulates surface runoff in the main urban area of Kunming. The results show that the calibrated proposed model is suitable for the main urban area of Kunming, with an average relative error of less than 15%. The location of paddy fields, grasslands, shrubs, and sparse woods from 1986 to 2014 has been significantly reduced, and the area has been transformed into urban construction land from the forest land. These encroachments may lead to future problems of natural resources and forest lands which would disturb the ecosystem completely.

Cities are the places where human activities have the most intense impact on the environment. Land use changes driven by urbanization and their environmental impacts are becoming more prominent for global warming [9]. Urbanization is affecting the structure and function of ecosystems at regional and global scales. The ecosystem is getting hampered by the all the activities done by the humans without caring about the ecological changes and their respective impacts on the environment [10]. The problem of surface water pollution is closely related to the changes in land usage. Land use changes in urban public space planning have a profound impact on the urban surface water environment which is mainly manifested in two aspects: surface runoff and water quality. The planning of public space has led to a significant increase in the impervious area of the urban area which has changed the temporal and spatial patterns of the water balance resulting in changes in the interface process of water conversion [11, 12]. The urban land usage process often simplifies the shape of the water area, thereby reducing the water area's ability to diffuse and degrade pollutants [13].

Many researchers have performed studies in the area of the research study of the paper. In [14], the authors used the GIS-based SCS-CN (soil conservation service-curve number) method to predict the water balance consisting of surface runoff, infiltration, and groundwater storage in Upper Cisadane Watershed. In [15], the authors presented the research about the relationship between water pollution and economic advancement in the lake. The authors used a regression model to establish the relationship between water quality parameters and GDP. The dataset is used to study records from 1991 to 2005. In [16], the authors predicted the water quality using long short-term memory neural networks. The results predict the quality of water with respect to target variables. The accuracy in prediction is measured by the statistical methods. In public space planning, with the expansion of urban construction land and industrial land, the large amount of waste water is generated by urban usage which affects the lives of people drastically [17]. The residues of water contain particulate matter, ammonium nitrogen, organic pollutants, and heavy metals [18]. As the pollutant load increases, the water quality deteriorates and surface water pollution becomes more serious [19]. The water environment and its pollution are leading environmental problems that are threatening human survival at present [20]. If we wish to safeguard the future, then corrective measures have to be taken now by predicting the controlled usage of urban land and water resources.

Based on the above studies, it is concluded that this area of research needs more new methods for prediction of land misusage to protect the environment for future generations. This paper predicts the impact of land use changes on surface water pollution in public space planning, laying a foundation for improving water resource pollution. The highlights of the work presented in this paper are listed below:

(i) The regression analysis on land use changes of different spatial scales with four surface water pollution indicators in the dry and wet seasons is carried out to obtain the regression of each water pollution indicator.

(ii) According to the determination coefficient, the determination coefficient of the proposed model uses the comprehensive pollution index method to predict the impact of land use changes on surface water pollution.

(iii) The experimental results show that the prediction accuracy of the proposed method is high and it is helpful in studying the impact of land use change on surface water pollution.

(iv) It can certainly help in decision making on the utilization of natural resources optimally to reduce the over-consumption of resources and to reduce pollution.

The next section is devoted to explaining land usage characteristics, followed by Section 3 which is devoted to discussing the prediction model. The results are discussed in Section 4. The conclusions are discussed in the last section of the paper.

2. Land Use Change Characteristics

Land usage changes involve many aspects, and the evaluation process is also very complicated. Therefore, the establishment of various types of land usages based on dynamic change models, characterized by abstraction, has an extraordinary effect on the land usage analysis. It is generally believed that there are three main processes of land use changes in public space planning such as time change process, space change process, and quality change process [21]. The overall trend of regional land use changes can be clarified by analyzing the total changes of different land use types in public space planning. This paper uses remote sensing images from 2015 to 2019 as the primary data based on existing research. The study is starting from the analyses of quantitative characteristics of land usage types and changes in land usage degree during different years.

2.1. Analysis of Land Use Quantity Change. The extent of land usage changes reflects the quantitative changes of various land use types in public space planning. Analyzing the area changes of various land use types can clarify the overall trend of land use changes in public space planning, and then it helps in understanding the advantages of land resources [19]. Its mathematical expression is given as

$$K = \frac{S_b - S_a}{T}, \tag{1}$$

where K represents the average annual change of a certain land use type in a certain research period; S_a, S_b represent the area of a certain land use type at the beginning and at the end of the study period; and T represents the number of years between the study period. Land use dynamic degree is a quantitative description of the land use changes in public space planning. It is usually used to compare the difference in land use changes in different periods and predict the trend of land use change in the future region [12]. The dynamic degree of a single land use type represents the change of a certain land use type in the public space planning within a certain time range, and its expression is given as

$$K_1 = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%, \tag{2}$$

where K_1 is the dynamic degree of a certain land use type in the study period and U_a and U_b represent the quantity of a certain land use type at the beginning and end of the study period, respectively. When the unit of T is set to year, it represents a specific type of land use in the study area changed to an annual rate of change of land use of a specific type [13].

Introduce the relative change rate of land use K_2 to quantitatively characterize the regional difference of a certain land use type change. The relative change rate of a specific land use type can be expressed as

$$K_2 = \frac{K_x}{K_y} = \frac{|U_b - U_a|/U_a}{|S_b - S_a|/S_a}, \tag{3}$$

where K_x and K_y are the dynamics of a certain land use type in a local area and the whole area, respectively; if $K_2 \rangle 1$, it means that the land use change rate of the study area in the public space planning is greater than the change rate of the entire area; if $K_2 \langle 1$, then the land use change rate in public space planning is lesser than the change rate of the entire area.

2.2. Analysis of Land Use Structure Change

2.2.1. Time Change of Land Use Structure. The land use structure is produced based on the various land use areas interpreted by remote sensing images in the public space planning of a city in 2015, 2016, 2017, 2018, and 2019 as shown in Figure 1.

From Figure 1, we can see that the proportion of forest land and urban land in the public space planning is relatively large. The proportion of grassland, water, and unused land in this study area is very small which is accounting for less than 2%.

Specifically, the proportions of construction land in public space planning show a slow-growth trend which is increasing from 2.01% in 2015 to 9.86% in 2019. The proportion of arable land has shown a slow decline from 46.48% in 2015 to 38.23% in 2017 and then to 34.67% in 2019. The proportion of woodland, grassland, water, and unused land area fluctuates with the time and environmental changes. The woodland area has first increased and then has decreased, increasing from 50.19% in 2015 to 55.44% in 2017 and then decreasing to 54.25% in 2019. Unused land occupies a small proportion of the area, and the change in proportion is relatively stable varying between 0.15% and 0.45%. The proportion of water area showed a trend of first decreasing and then increasing. In 2015, its area proportion was 0.8%, and by 2017, it was reduced to 0.45%.

2.2.2. Land Use Change Transfer Analysis. The internal transfer analysis of various land use types is generally carried out through the transfer matrix. The transition matrix model is shown in the following equation:

$$A = \left\{ \begin{array}{cccc} A_{11} & A_{11} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{array} \right\}. \tag{4}$$

In order to obtain the quantitative relationship between the conversions of various types of land use at different stages in the public space planning, ArcGIS software is used to perform spatial superposition calculations on the land use classification results of two adjacent periods to obtain the land use change in the public space planning from 2015 to 2019. By suing the transfer matrix, the corresponding proportions of various land usage types are determined. From Table 1, it can be seen that the transfer area of various land use types in public space planning is different.

From the perspective of the number of transfers, the most transferred area is arable land, which is 122.217 km^2. Grassland and woodland are the less transferred areas, which are 3.581 km^2 and 2.393 km^2, respectively. The most transferred areas are forest land and construction land. The transferred areas from other land use types are 75.207 km^2 and 60.140 km^2, respectively. The transferred areas are 6.306 km^2 and 4.756 km^2, respectively, followed by unused land and grassland. The areas with the less transferred area are cultivated land and water area, 1.922 km^2 and 2.706 km^2, respectively [15]. In terms of the percentage of transfer, grassland and unused land have the most significant transfer ratio with 97.90% and 94.19%, respectively, followed by the farmland with transfer-land ratio of 18.01%, where the

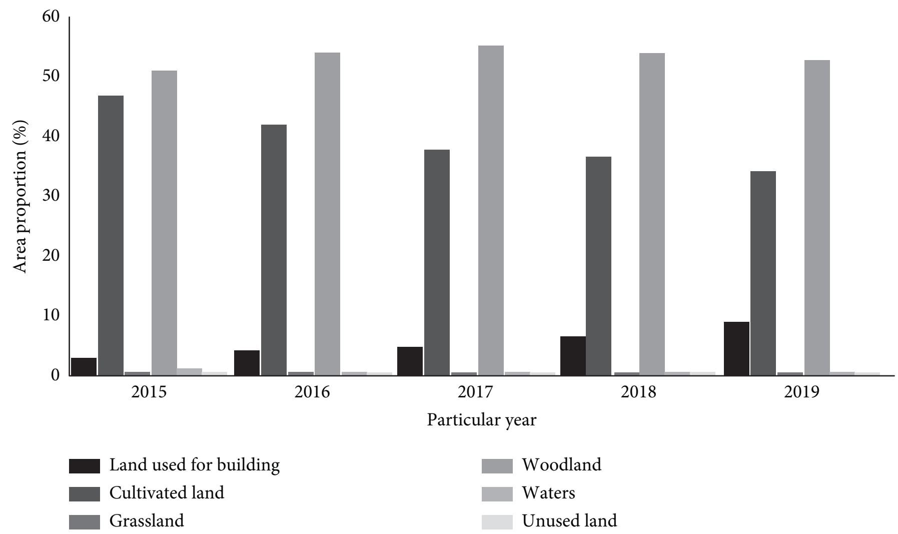

Figure 1: The structure of land use types from 2015 to 2019.

smaller transfer-land area belongs to the forest land, then the proportion of construction land is 0.33% and 14.72%, respectively. The largest transfer rate of the area is construction land, with a transfer rate of 71.13%, followed by water and unused land, with transfer rates reaching 40.78% and 30.24%. The farmland and forest land with the smallest transfer ratio are 0.34% and 6.68%, respectively.

From the perspective of the transfer direction, the total amount of construction land transferred out is relatively small and the transferred part is mainly converted to grassland with a transfer volume of 3.317 km^2. The transfer of arable land is relatively large where it is mainly converted to construction land and forest land. 58.324 km^2 of arable land is converted to construction land, and 56.853 km^2 of arable land is converted to forest land and a small amount of arable land is converted to other land types. The amount of grassland transfer is relatively small with 1.703 km^2, 0.708 km^2, 0.469 km^2, 0.291 km^2, and 0.077 km^2 being converted into forest land, water area, grassland, construction land, and cultivated land, respectively. The wetland is mainly converted into forest land and unused land with the converted areas being 5.089 km^2 and 3.948 km^2, respectively. The change in the woodland area is also small with 1.399 km^2 and 0.358 km^2 of woodland being converted into construction land and unused land. The area of unused land is mainly converted to forest land with a transfer volume of 1.274 km^2. In addition, a small amount of unused land is converted to other land types.

To sum up, during 2015–2019, the land use changes in public space are mainly cultivated land, construction land, and forest land. The conversion of cultivated land to construction land is the most important feature of land use change in the study area at this stage. The main reason for this change is that with the development of urbanization, the expansion of construction land has occupied a large amount of farmland which has reduced the area of arable land and eventually the construction land has been expanded [17].

2.3. Analysis of Land Use Degree Change. The comprehensive degree index model of land use can reflect the depth and breadth of land use in public space planning. Using the comprehensive analysis method of land use degree, the land use degree is divided into four grades according to the comprehensive influence of various social factors and different indexes are assigned to each grade as shown in Table 2.

In the research area, the comprehensive index of its land use degree, the amount of change of land use degree, and the rate of change can quantitatively reveal the degree of regional land development and change trend. The quantitative expression of the comprehensive index L_d of land use degree is given in the following equation:

$$L_d = 100 \times \sum_{i=1}^{n} A_i \times C_i, \quad (5)$$

where L_d represents the comprehensive index of land use degree in the study area, A_i represents the i^{th} type land use classification index; C_i represents the proportion of the i^{th} type land use area; and n represents the regional land use degree classification number.

The mathematical expression of land use degree change is given by

$$L_{b-a} = L_b - L_a = 100 \times \left(\sum_{i=1}^{n} A_i \times C_{ib} - \sum_{i=1}^{n} A_i \times C_{ia} \right). \quad (6)$$

The mathematical table of land use degree change rate R is given by

$$R = \frac{L_b - L_a}{L_a} \times 100\%. \quad (7)$$

In (6) and (7), L_a, L_b represent the comprehensive index of the degree of land use at the beginning and end of the study period. If the calculation result is $L_{b-a} \rangle 0$ or $R \langle 0$, it indicates that the regional land use in this time period is in the development period; otherwise, it is in the adjustment period or decline period.

Table 1: The proportion of land transfer from its usage from 2015 to 2019.

2015–2019	Construction land	Arable land	Grass	Waters	Woodland	Unused land	Total transfer land
Construction land	25.065	0.371	3.317	0.265	0.288	0.085	4.326
Proportion (%)	85.31	1.26	1.13	0.90	0.98	0.29	14.72
Arable land	58.324	558.397	0.716	1.396	56.853	3.328	122.217
Proportion (%)	8.59	82.28	1.11	0.21	8.38	0.49	18.01
Grass	0.469	0.291	0.077	0.708	1.703	0.411	3.581
Proportion (%)	12.82	7.92	2.10	19.45	46.66	11.24	97.90
Waters	0.127	0.114	0.286	3.948	5.089	5.124	7.740
Proportion (%)	1.09	0.98	2.45	33.78	43.54	18.17	66.22
Woodland	1.399	0.118	0.223	0.295	730.359	0.358	2.393
Proportion (%)	0.19	0.02	0.03	0.04	99.67	0.05	0.33
Unused land	1.221	1.029	0.114	0.042	1.274	0.227	3.680
Proportion (%)	31.25	26.34	2.92	1.08	32.61	5.81	94.19
Transfer in total	60.140	1.922	4.756	2.706	75.207	6.306	
Proportion (%)	71.13	0.34	6.68	40.78	9.41	30.24	

Table 2: Ten land use categories and classification.

	Unused land level	Land grade of forest, grass, and water	Agricultural land grade	Construction land grade
Land use types	Unused land	Woodland, grassland, and water area	Cultivated land	Land used for building
Graded index	1	2	3	4

3. Prediction of Impact of Land Use Changes on Surface Water Pollution

3.1. The Relationship between Land Use Change and Surface Water Pollution. On the basis of the analysis in Section 2 on land use change characteristics, we explore the relationship between land use change and surface water pollution. We conduct exponential regression analysis of land use change and surface water pollution indicators at different spatial scales and select a curve with a higher degree of fit. Figure 2 shows the relationship between land usage changes and the surface water pollution.

Since the regression analysis results between land use changes and surface water pollution indicators at different spatial scales are similar due to space limitations, this study lists the regression analysis results between land usage changes and water pollution indicators. It can be seen from Figure 2 that land use changes of different spatial scales have prominent positive effects on surface water pollution indicators: the greater the intensity of land use, the lower the concentration of DO (dissolved oxygen), and the higher the concentration of surface water pollution indicators, the worse the water quality. It shows that the increase in land use intensity in public space planning will lead to the deterioration of surface water pollution.

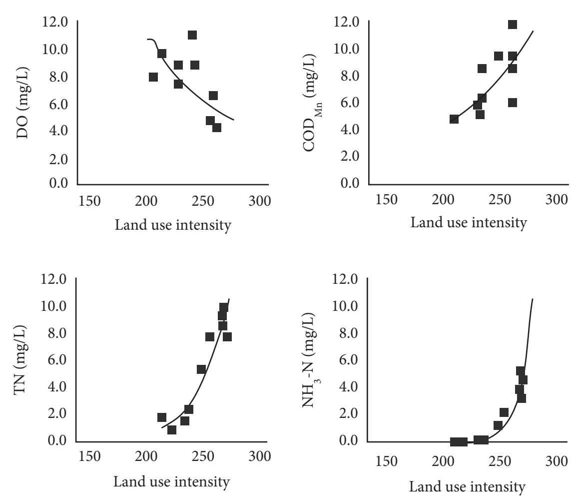

Figure 2: The relationship between land use change and surface water pollution.

3.2. Scale Dependence of the Impact of Land Use Change on Surface Water Pollution. To explore the scale dependence of land use change on surface water pollution in the dry and wet seasons, the land use changes at different spatial scales have been analyzed with 4 water pollution indicators. From empirical study, the water pollution at different spatial scales is obtained. The coefficient of determination R^2 of the index regression model is shown in Table 3.

The size of the determination coefficient is compared to identify the strength of the impact of land use changes on surface water pollution. From the data in Table 3, it can be observed that the impact of land use change on surface water pollution also has an obvious scale effect. As the spatial scale increases, the negative effect of land use change on surface water pollution gradually strengthens. Regardless of the wet season or the dry season, the overall judgment coefficient is relatively large, that is, land use changes have the greatest impact on surface water pollution and this scale is the dominant scale for land usage intensity to affect surface water pollution. From the perspective of the difference in the determination coefficient of the regression model, the wet season is generally larger than the dry season, indicating that the impact of land use changes on surface water pollution is

Table 3: Determination coefficients of regression models of surface water pollution indicators at different spatial scales.

Season	Water quality index	50 m	100 m	200 m	300 m	400 m	500 m	600 m	Watershed
Wet season	TN	0.640	0.704	0.786	0.835	0.839	0.853	0.871	0.902
	NH_3-N	0.594	0.674	0.777	0.829	0.839	0.860	0.876	0.899
	COD_{Mn}	0.565	0.625	0.682	0.711	0.720	0.736	0.759	0.818
	DO	0.197	0.237	0.349	0.433	0.464	0.488	0.475	0.485
Dry season	TN	0.639	0.684	0.749	0.786	0.798	0.810	0.824	0.869
	NH_3-N	0.667	0.741	0.829	0.879	0.882	0.894	0.906	0.928
	COD_{Mn}	0.525	0.583	0.588	0.592	0.573	0.577	0.601	0.587
	DO	0.583	0.607	0.662	0.670	0.652	0.658	0.637	0.62

Table 4: Correlation coefficients among surface water pollution indicators.

	DO	COD_{Mn}	NH_3-N	TN	Q
DO	1				
COD_{Mn}	−0.537**	1			
NH_3-N	−0.721**	0.676**	1		
TN	−0.535*	0.580**	0.884**	1	
Q	−0.719**	0.700**	0.955**	0.678**	1

**represents a significant correlation at the 0.01 level; *indicates a significant correlation at the 0.05 level.

seasonally different. The impact of the wet season is stronger than the dry season.

The impact of land use change on surface water pollution is generally the largest; the indicators for specific surface water pollution are slightly different. In the wet season, all indicators consistently show that the impact of land use change is the strongest. The dry season represents COD_{Mn}, which is the amount of organic matter polluted in surface water. The DO, which characterizes the oxygen content of river water bodies, is affected the most by land use changes of 300 m and 600 m along the bank.

3.3. Prediction of Impact of Land Usage Changes on Surface Water Pollution. Single-factor prediction is a commonly used method of surface water pollution prediction. It selects the worst water pollution index level in the surface water pollution level prediction as the water pollution level of the entire surface water quality monitoring section. When the single-factor evaluation method is used to predict surface water pollution due to land use changes, the annual average values of various water pollution indicators at each surface water quality monitoring section are calculated, respectively. Various surface water pollution levels are predicted according to surface water quality standards. It was found that the NH_3-N or TN of the surface water quality monitoring sections in each region exceeded the limit of the V-type water pollution level. Therefore, if the single-factor evaluation method is used, then all the factors affecting the water quality cannot be considered and the surface water quality monitoring cannot be performed accurately. The comparison of water quality between the two cannot reflect the overall water quality of the study area.

Therefore, this paper uses the comprehensive pollution index method to predict the impact of land use changes on surface water pollution based on the determination coefficients of the regression models of various water pollution indicators and combines various surface water pollution indicators to reflect the water quality status comprehensively. The comprehensive pollution index method standardizes several surface water pollution indicators, superimposes each standard value, and then takes the average value. The larger the value, the worse the water quality. Then, construct a prediction model for the impact of land use changes on surface water pollution in public space planning, and the formula is shown in the following equation:

$$Q = \frac{1}{n}\sum_{i=1}^{n}\frac{c_i}{s_i}, \tag{8}$$

where Q is the comprehensive pollution index and s_i is the water quality standard concentration value, and its value is selected as the surface water quality standard III water-like limit. Under normal circumstances, the higher content of DO in surface waters indicates the better quality of water. Therefore, for standardizing DO, c_i/s_i is substituted into the formula. The Spearman rank correlation analysis method is used to conduct a pairwise correlation analysis on the annual averages of 4 surface water pollution indicators in 22 water quality monitoring sections from 2015 to 2019. Table 4 shows the correlation coefficients among surface water pollution indicators.

There is a significant negative correlation between NH_3-N and DO, with a correlation coefficient of 0.721, indicating higher concentration of NH_3-N in water quality and lower content of DO.

The results of correlation analysis between comprehensive pollution index Q and water pollution indicators show that NH_3-N, TN, and Q have the highest correlation with correlation coefficients of 0.955 and 0.880, respectively. These two water pollution indicators are the factors that have the greatest impact on Q. Therefore, the key to improving

Figure 3: Sampling environment.

Table 5: Related statistics of study area.

Related indicators	2009	2019
Scale of built up area (km^2)	8.0	47.0
Population of built up area (10000)	1.8	26.0
Municipal roads (km)	3.5	70.0
Commercial housing area ($10000\,m^2$)	26.1	387.0
Cultural and educational facilities ($10000\,m^2$)	44.0	465.0
Medical and health facilities ($10000\,m^2$)	0.1	12.1
Commercial supporting facilities ($10000\,m^2$)	1.2	40.3
Bus lines (piece)	2.0	17.0

surface water pollution is the need to control the concentration of NH_3-N and TN.

4. Simulation Experiment Analysis

4.1. Sampling Environment. In order to verify the effect of the prediction of the impact of land usage changes on surface water pollution in the public space planning studied in this paper, a simulation experiment is carried out. The sampling point of the study area is from May 2018 to March 2019 collected once a month, a total of 11 sets of data. The sampling environment is shown in Figure 3. Table 5 shows the relevant data statistics of the study area in 2009 and 2019.

4.2. Data Processing. The data used in this research study are extracted from GIS software. Before making use of GIS software, the relevant format and resolution need to be set to meet the requirements of the output. The specific conversion format is shown in Table 6. Land use changes have an important impact on surface water pollution, and it is also an indispensable GIS model for data acquisition. The preprocessing of data is made by treating the missing values in the data. The data is scaled up to balance the data before applying machine learning based regression technique. The forecasting of the land usage is based on the data collection, its processing, and training model which analyse the preprocessed data. Once the data are ready, the software applies the forecasting models to draw output and to make appropriate decisions.

Table 6: Data conversion format.

Data	Resolution (m)	Format	Source
Digital elevation map	25	Grid	Data center for resources and environmental sciences
Land use map	30	Grid	Resource and Environmental Science Data Sharing Center of an Academy of Sciences
Surface water pollution type map	1000	Grid	Water Pollution Science Data Center China

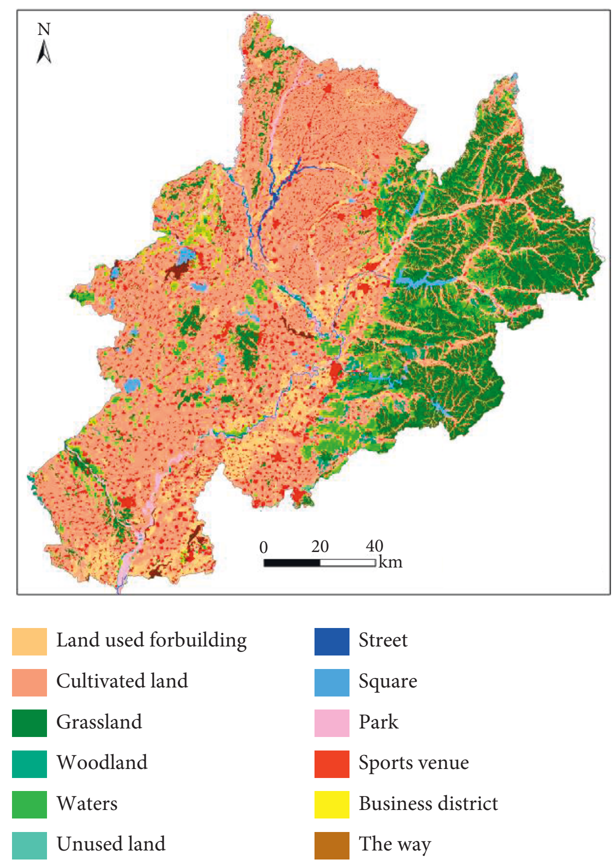

Figure 4: Distribution of land types.

The resolution of the land use map obtained in this paper is 30 meters, and the distribution of land types is shown in Figure 4.

4.3. Prediction Accuracy. According to the land type, distribution, and sampling environment, the impact of land-use change on surface in the Beijing-Tianjin-Hebei urban agglomeration has been studied in literature [8] and the impact of land-use changes on surface runoff in the main urban area of Kunming City is studied in literature [9] which are used as comparison methods. The prediction accuracy of the impact of land use change on surface water pollution is used as the

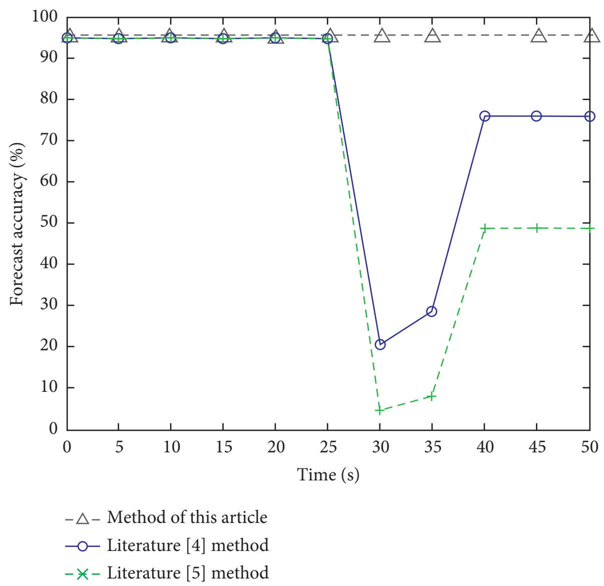

Figure 5: Comparison results of prediction accuracy.

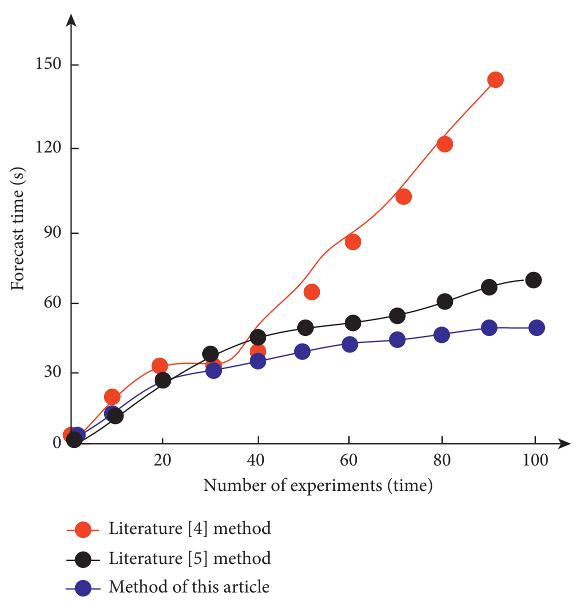

Figure 6: Comparison results of forecast time.

experimental index and the method used in this paper is compared and analyzed with the existing literature mentioned in references [8, 9]. The comparison result is shown in Figure 5.

According to Figure 5, the prediction accuracy of the impact of land use change on surface water pollution of the research method in this paper has remained stable with increase in prediction time. The prediction accuracy is 95% which is highest among the methods taken for comparative study. It is observed that literature [8] and literature [9] methods show lower prediction accuracy in comparison to the proposed method in this article. The surface water pollution shows a downward trend when the prediction time is 25 s for methods given in reference [8] and reference [9], and the prediction accuracy of the proposed method for analyzing the impact of land use changes on surface water pollution is relatively high.

4.4. Forecast Time. The forecasting time for comparative results is shown in Figure 6. According to Figure 6, the prediction time of the impact of land use change on surface water pollution is within 45 s by the research method of this paper. In [8], the prediction time of the impact of land use change on surface water pollution is 150 s, and in reference [9], the prediction time of the impact of land use change on surface water pollution is within 70 s. Therefore, in this paper, the prediction time of the impact of land usage changes on surface water pollution is shorter than that of the research method used by the authors in [8, 9]. The research method used in this paper can improve the efficiency of predicting the impact of land use changes on surface water pollution.

5. Conclusions

There is a close relationship between the heavily polluted surface water in public space planning and the surrounding land use patterns. Waters in different locations have different types and changes of surrounding land use, and their pollution levels and major pollutants are also different. The typical variables between pollutants and land use types in other waters are also different, but they generally have certain similarities. Industrial and mining storage land, urban construction land, and transportation land have a close positive correlation with pollutants such as oxygen-consuming organics, heavy metals, and petroleum in waters. In contrast, ecological land such as forest land, green land, and waters is related to heavy metals and oxygen-consuming organics, and there is a close negative correlation between them. Urban expansion and the increase in land use intensity are reasons for the aggravation of surface water pollution. Ecological lands such as gardens and water areas have a certain function of purifying surface water pollution. The research method used in this paper used regression analysis to predict the impact of land use changes on surface water pollution which generates accurate predictions by giving 95% accuracy in output. The reasonable adjustment of urban land usage structure and layout plays a major role in protecting the surface water environment; therefore, it is important to predict the consequences of land usage on the environmental changes by using computational techniques for decision making.

Data Availability

The data are available on the request to the authors.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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