Research on Improved Strategy of Soil Heavy Metals based on Neural Network Model

Yiting Wang¹, Tingting Wang², Xiaolu Qiu³, Zhihong Ma⁴, Cuiping Zhao^{4*} ¹School of Agronomy and Resources Environment, Tianjin Agricultural University, Tianjin, 300384, China ²School of Computer and Information Engineering, Tianjin Agricultural University, Tianjin, 300384, China ³School of Economic and Management, Tianjin Agricultural University, Tianjin, 300384, China ⁴School of Basic Sciences, Tianjin Agricultural University, Tianjin, 300384, China * Corresponding author

Abstract: Today, as the process of urban industrialization industrialization progresses, heavy metal pollution in large areas of soil in Beijing, trend is not encouraging, and hindering the process of urban development. To study how to improve soil conditions, In this paper, we used the mathematical modeling method, and using Principal Component Analysis Method and Neural Network Model. Results show: The pollution of heavy metals in urban soil has not improved. According to the specific situation of Beijing, we make the following recommendations: the focus of governance is on improving the removal rate of pollution in Hg and Cu, will effectively improve the condition of heavy metal pollution in soil. In this case, we use Matlab to verify the usefulness of the recommendations. The proposed changes have a reliable reference value for improving soil quality.

Keywords: Evaluation of heavy metal pollution in soil; Principal component analysis method; Neural network model; SPSS; MATLAB

1. Introduction

In recent years, the problem of heavy metal pollution in soil has become a hot topic in various countries in the world. Humans and nature should live in harmony, but with the continuous advancement of the process of urban industrialization, large areas of land have been heavily polluted by heavy metals, and the soil heavily polluted by heavy metals can not only not build land use projects, the heavy metals in the soil will also enter deeper groundwater with rainwater runoff or the use of their own fluidity, resulting in double pollution, which has an irreversible impact on urban development. If it is not taken seriously, then humanity will pay a serious price for it.

In order to put forward the feasibility recommendations, taking Beijing as an example, we use Multi-Factor comprehensive model to evaluate the heavy metal pollution in urban soil and using Neural Network Model to simulated the condition of heavy metal pollution in urban soil .In this way, we can not only predict its dynamic change as the decision-making basis of urban construction planning, but also verify the effectiveness of improvement measures.

2. The Establishment and Verification of Multi-factor Comprehensive Model

2.1. Modeling assumption

Assuming the reliability of the measured value of soil heavy metals over the years. Assuming there are no major decision changes in the region over the next few years. Assuming the region's economic and population growth shows a steady trend.

2.2. The definition and explanation of symbols

Symbols	Definition
P_i	Pollution index of contaminants i in soil
Q_i	Measured concentration of contaminants i in soil, mg/kg
S_i	The evaluation criteria of contaminant i, mg / kg
X _a	The background values of soil environment

Lable It life definition and explanation of by moois	Table	1.	The	definition	and	ex	planation	of	symbols
--	-------	----	-----	------------	-----	----	-----------	----	---------

HK.NCCP

X_{c}	Mild contamination value of soil	
X_{e}	Severe contamination value of soil	

2.3. The establishment of evaluation model

2.3.1. The calculation of multi-factor comprehensive pollution index

According to the soil background value of Beijing and the measured value of heavy metal content in soil over the years calculate the single factor index. In this paper, five kinds of heavy metals, such as Hg, Cu, Pb, Cr and Cd, are selected as evaluation indexes. Calculating the pollution index of heavy metals in Beijing area.

It is worth noting that when the measured values are different from the background value, the mild contamination value, and the heavy contamination value, the index needs to be calculated using various calculation formulas:

When
$$Q_i \leq X_a$$
, $P_i = \frac{Q_i}{X_a}$

When
$$X_a < Q_i \le X_c$$
, $P_i = 1 + \frac{Q_i - X_a}{X_c - X_a}$

When
$$X_c < Q_i \le X_e$$
, $P_i = 2 + \frac{Q_i - X_c}{X_e - X_c}$

When
$$Q_i > X_e$$
, $P_i = 3 + \frac{Q_i - X_e}{X_e - X_c}$

Using SPSS to analyze the Principal Component Analysis of the results, the results are as follows:

		Initial eiger	ivalues	Extra	acting square	d and loading	Rotating squared and loading			
Composition	Total	Variance	Accumulation	Total	Variance	Accumulation	Total	Variance	Accumulation	
		of %	of %		of %	of %		of %	of %	
1	2.910	58.282	58.282	2.910	58.207	58.207	2.144	42.874	42.874	
2	1.044	20.871	79.153	1.044	20.871	79.079	1.810	36.204	79.079	
3	.858	17.163	96.316							
4	.188	3.375	99.691							
5	.016	0.309	100.000							

 Table 2. The result of principal soil composite index

From the table above, we know that extracting 2 factors from the factor analysis, the variance interpretation rate after the factor rotation is 42.874%, 36.204%, and the cumulative variance interpretation rate after rotation is 79.079%. That is, four factors in this example extract a total of 79.079% information.

Since two factors extract a total of 79.079% information, the actual study will assume that the factor represents all indicators (the total variance interpretation rate should be 100%, not 79.079%), so a weighted conversion operation is required here. That is, the variance interpretation rate of two factors should be 55.451% and 45.782%.

The results show that the weight ratio of Hg, Cu, Pb, Cr and Cd is about 0.58, 0.20, 0.17, 0.03 and 0.003. It is not difficult to see that the degree of heavy metal pollution in soil is more correlated with Hg content, followed by Cu. In order to evaluate the comprehensive pollution degree of heavy metals in soil of Beijing, the Soil Composite index was calculated by using the pollution index and weight of each pollutant in soil:

$$P = \sum_{i=1}^{n} W_i P_i$$

Table 3. Soil composite index

Year	Р	Year	Р	Year	Р
2005	1.065	2006	1.105	2007	1.275
2008	1.611	2009	1.573	2010	1.614
2011	1.165	2012	1.295	2013	1.611
2014	2.677	2015	3.376	2016	3.453
2017	3.396	2018	3.457		

2.3.2. The establishment of neural network model

The commonly used Neural Network Model is divided into two types according to its dynamic neural network, which is different from the method of realizing system dynamics: One is a regression neural network, a dynamic network composed of static neurons and network output feedback, and the other is a neural network formed by neuronal feedback; NAR Neural Network is one of the first classes, Because of its advantages such as fitting effect, accuracy and low impact on data, widely used in nonlinear dynamic systems. The NAR neural network includes the input layer, the implicit layer, the output layer, and the input delay, as shown in the figure:





Figure 1. Neural network model

Based on the results of the evaluation of the 2005-2018 Beijing Soil Composite Index, here we use MATLAB to establish a Neural Network Model to predict changes in soil heavy metal content in recent years:



Figure 2. The predictive results of neural network model

According to the prediction results of neural network, the comprehensive evaluation index of soil heavy metals in the next 5 years shows a steady upward trend, which shows that if not controlled, the heavy metal pollution of soil in Beijing will become more and more serious.

3. Model Modification Proposal and Analysis

The above results have shown that Cu and Hg are important factors leading to the rise of heavy metal pollution index in Beijing, and the main source of Hg pollution is inappropriate treatment of domestic waste, Cu mostly comes from metal factory. Experiments have shown that, through effective treatment, Hg emissions will be reduced to $50\% \sim 70\%$, removal rate of Cu up to $5\% \sim 35\%$.

Then if the intermediate value of removal rate of Hg and Cu removal rate is taken to simulate the management policy of Beijing after five years, the effectiveness of the improvement measures can be verified. As shown in the figure, by amending, the 2020-2015 soil Pollution index in Beijing showed a wavy decline, and if the timeline was stretched, it is highly likely to reduce the amount of heavy metals in the soil.



Figure 3. The revised predictive results of neural network model

4. Conclusion

The degree of heavy metal pollution in soil of Beijing was evaluated by Principal Component Analysis method, and the main factors affecting soil pollution were found. Then we improved the removal rate of the main factors, aiming to improve the soil quality and verify the effectiveness of the control measures through the Neural Network Model. Finally, we put forward more scientific and reasonable suggestions to improve soil quality.

References

 Chai L.L., Cui X.T. Evaluation of heavy metal pollution and potential ecological hazards in urban soil of Baoding. Journal of Safety and Environment. 2019, 19, 607-614.

- [2] Dai J., Wang X.Y., Du W.Q. Analysis of spatial and temporal evolution of land use change and ecological service value in Jinan. Science of Environmental Protection. 2019, 45, 6-15.
- [3] Zhao L., Liang Y.P., Chen Q., Xu Q., Jing H.W. Spatial distribution characteristics, pollution assessment and source analysis of heavy metals in urban green soil in Beijing. Environmental Science. 2019, 1-13.
- [4] Liang R.F., Comparative study on cross-variety arbitrage strategy of futures based on BP neural network model and NAR dynamic neural network model. Zhejiang University of Finance and Economics. 2016.
- [5] Li X.Y., Chen T.B., Lei M., Guo Q.J., Song B., Zhou G.D., Xie Y.F. Characteristics of heavy metals accumulation in soil of Beijing urban areas under different land use patterns. Journal of Environmental Science. 2010, 30, 2285-2293.
- [6] He L.L., Li D.M., Wu G.L. Research status and prospect of heavy metal pollution in urban soil in China. Soil Bulletin. 2008, 1210-1216.