Research Progress and Prospects of Soil Pollution Assessment and Prediction Models

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Abstract. Soil pollution has become a worldwide environmental problem. The assessment and prediction of soil pollution status is also the focus of scholars at home and abroad. In general, the soil pollution assessment and prediction has experienced the field investigation phase, the statistical analysis phase and the process simulation phase, each of which reflects different levels of the discipline. With the enhancement of today's big data processing technology and management capabilities, as well as the increasing popularity of aerial remote sensing (RS) and unmanned aerial vehicle (UAV) low-altitude RS applications in the environmental field, it is necessary to integrate these new technologies in time to develop highly efficient models to provide strong technical supports for soil pollution control and restoration decision-making.

1. Introduction
With the irrational development and utilization of mineral resources, the large-scale application of chemical fertilizers and pesticides, the rapid development of industrialization and urbanization, soil pollution is becoming increasingly serious. In recent years, all countries in the world have attached great importance to the treatment of polluted soil. The Chinese government once again emphasized the importance of ecological civilization construction in the report of the 19th National Congress of the Communist Party of China, and proposed that "building ecological civilization is the millennium plan for the sustainable development of the Chinese nation." In 2014, the Ministry of Ecology and Environment (MEE, formerly the Ministry of Environmental Protection) led the development of the Soil Pollution Prevention and Control Action Plan, which pointed out the direction for the prevention and treatment of soil pollution. In 2018, the MEE approved two standards for soil pollution risk management and control. Namely, “Soil Environmental Quality-Risk Control Standard for Soil Contamination of Development Land (Trial)”, “Soil Environmental Quality-Risk Control Standard for Soil Contamination of Agricultural Land (Trial)”, and the “Technical Guidelines for Environmental Impact Assessment-Soil Environment (Trial)” were issued in the same year. It can be seen that the country has already mentioned soil environmental protection to an unprecedented strategic height. It is imperative to carry out soil environmental protection and soil restoration in an all-round way.

The 2014 China soil pollution data released by the Ministry of Ecology and Environment indicates that the total soil over-standard rate is 16.1% in the survey area of about 6.30×10⁶ km². In China, 19.4% of cultivated soil is polluted, among which inorganic pollution is the most, and organic and composite pollution is relatively small. The number of inorganic pollutants exceeding the standard point...
accounted for 82.8% of all over-standard points, and the over-standard rates of eight inorganic pollutants such as Cd, Ni, As, Cu, Hg, Pb, Cr and Zn respectively are 7.0%, 4.8%, 2.7%, 2.1%, 1.6%, 1.5%, 1.1%, and 0.9%, so heavy metals are the main elements causing soil pollution in China. Heavy metals are one of the soil environmental pollutants that seriously endanger ecological safety [1]. They can change the chemical composition of soil and directly or indirectly destroy the ecological structure of soil. The accumulation and migration of heavy metals in soil not only affect the growth and development of animals and plants and the quality of agricultural products, but also directly harm human health through the food chain [2]. So, the assessment and prediction of the distribution and migration process of pollutants in soil, especially heavy metals, has been the focus of scholars at home and abroad [2-6].

2. Model research progress

Researches on soil pollution assessment at home and abroad have been in existence for decades. They have experienced field investigation stages based on field monitoring, statistical analysis stages based on black box models, and mechanism research stages based on process simulation.

2.1. Field investigation stage

The field investigation method is based on the measured data, and the measured data is directly compared with the soil environmental standard value or background value, or a simple index (such as the standard occupation ratio) is used to statistically analyze the measured data. Then the assessment conclusion of soil pollution status in a certain region can be gotten. This method is simple and straightforward, but it demands a large funds investment and long investigation time, and usually only describes the current status of pollution, does not have a predictive function, and is usually used in small regions.

2.2. Statistical analysis stage

In the commonly used assessment and prediction models, the empirical statistical models focus on the empirical statistical relationships between soil pollutants and their various influencing factors, such as the TELEMAC 2D-SUBIEF-MICROPOL model for calculating the migration of particulate sediments in riverbeds [7-8], STUMP model for calculating the migration behavior of particulate or dissolved pollutants [9-10], pollution index model [3,11], geo-accumulation index model [12-13] and risk assessment index model [14-15]. The advantage of the statistical model is that it is simple and convenient to apply. It is suitable for areas with good research foundation and abundant monitoring data. The disadvantage is that it dependsents on the measured data, and the regional applicability is poor. In the absence of data, it is very difficult to apply.

2.3. Mechanism research stage

Process models are based on the basic theory of the migration and transformation of pollutants in the soil, and simulate the process of soil pollution. For example, the Convective-Dispersive Model [16-18] can simulate the migration and transformation of dissolved and adsorbed heavy metals in porous media.

In recent years, models based on stochastic processes, neural networks, and fuzzy theory have also been used for soil pollution simulation and prediction [19-20], and have shown potential in describing the spatial distribution of pollution. The relationships between single impact factors and soil pollutant have also been studied intensively [21-22].

3. Research trends

In summary, the soil pollution assessment and prediction researches have been carried out on different spatial scales and made a series of important progress. However, these studies have deficiencies in varying degrees. Here are a few important issues to discuss.
3.1. Accuracy issues of prediction
In practical applications, the parameters in the process models are difficult to truly reflect the temporal and spatial changes of pollutants and media, and the accuracy of prediction is greatly affected by the parameters [23-24]. Whether it is a statistical model or a process model, since their parameters depend on the characteristics of the applied region, a large amount of measured data should be used to verify the parameters. Otherwise, the credibility of the prediction results is difficult to guarantee.

Due to the limitation of the number of field monitoring points and the uniformity of the point distribution in a given scale area, as well as the high input constraints of laboratory observations, the results of soil pollution prediction cannot be satisfactorily verified in many cases. On the other hand, the use of data from field monitoring for large-scale soil pollution assessments also presents difficulties due to the point number, location and regional differences in monitoring sites. In addition, due to the spatial scaling effects of soil pollution, the migration and transformation process of soil contaminants at different spatial scales are affected by different factors. Therefore, the data obtained in different scales will have spatial scaling effects which affecting the model’s structure and parameters. All of these indicate that it is very difficult to accurately predict soil pollution under different scale conditions under existing conditions.

3.2. Regional versatility of the model
Since the construction process of the existing models is mostly based on a specific region, the structural form of the model is different, and the versatility of the model is limited. Due to the natural, social and economic differences between different regions, models built in one region are difficult to apply to other regions. Although the process models have deeper researches on the mechanism of pollutant migration and transformation, the model structure is also relatively versatile. However, when such models are used in different regions, the parameter verification is complex, and it is difficult to have obvious versatility. The statistical analysis models obtain statistical disciplines based on the characteristics of different regions, and have obvious regional characteristics. So, model parameters and even model structures may need to be adjusted when applied to new regions. The research on soil pollution in a large scale is relatively weak, among which, semi-quantitative analysis is still the main method, and the versatility of the model is even worse. Therefore, the development of an assessment and prediction model with strong “transplantation” ability is the key content of future soil pollution research.

3.3. Spatial scale conversion problem of the model
Soil properties have spatial variability [25], and the scale factor of the study data affects the prediction of soil properties [26-27], so the migration and transformation process of pollutants in the soil also has spatial scaling effects. Studies show that the spatial variability of soil properties is a function of scales [28-29]. At different scales, the autocorrelation degree of the same variable is very different [30]. With the sampling interval increasing, the features at smaller scales will be masked.

At present, the spatial scaling effect of soil properties has been widely studied in soil nutrient, water, salinity, soil erosion and other aspects [31-36], but it is still less considered in soil pollution researches [37-38]. In addition, in the existing soil pollution prediction models, models of different scales have great differences in model structures, factor types and even method ideas, and can only be applied to their corresponding spatial scales. The correspondence between the factors affecting soil pollution at different scales and how to carry out scale conversion are still difficult in the model researches. Therefore, the development of an assessment and prediction model with scale conversion applicability has great significance in both soil pollution researches and soil treatment practices.
4. Conclusions and prospects

(1) The existing soil pollution assessment and prediction models are still difficult to overcome the regional versatility and spatial scale conversion, and most of the models have high requirements on data, and are difficult to meet the requirements of current soil pollution control practices.

(2) By studying the natural factors and human activity factors affecting soil pollution at different spatial scales, it is helpful to understand the spatial scaling effects of soil pollution, so as to study and develop an assessment and prediction model applicable to different spatial scales, and overcome the scale constraints of the existing models.

(3) The purpose of soil pollution assessment and prediction is usually to find out the degree of soil pollution in a certain area and provide technical supports for the decision on pollution control. Therefore, we can consider avoiding the idea of “precisely predicting” and instead predict the relative extent and trend of soil pollution. On the one hand, this method can ensure the prediction efficiency of the model and reduce the input of a large number of prediction parameters. On the other hand, the stability of the model is high and the accuracy of the output is guaranteed.

(4) With the current enhancement of big data processing technology and management capabilities, as well as the increasing popularity of aerial remote sensing and UAV (unmanned aerial vehicle) low-altitude remote sensing applications in the environmental field, the hierarchical management of large-scale spatial data is achievable. Through a powerful database and advanced data update methods, it can realize large-scale soil pollution dynamic assessment and prediction, thus providing powerful technical supports for the management department to formulate soil pollution prevention programs and decision-making.

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