ISSN: 2710-0588

Research Progress and Prospects of the Geographical Detector

Xueyi Wang

North China Electric Power University, Beijing, China

Abstract

Geographical detectors have become a widely used statistical tool in soil science for identifying dominant factors and interactions driving spatial differentiation of soil properties. This paper systematically reviews the basic principles, core functions (factor detection, interaction detection, risk area detection, and ecological detection), and application progress of the geographical detector in soil heavy metal pollution identification, soil erosion risk assessment, and digital soil mapping. By analyzing existing case studies, we summarize current limitations including sensitivity to discretization of continuous variables, scale dependence, lack of causal inference, insufficient characterization of interaction mechanisms, static single-time-snapshot analysis, and absence of systematic uncertainty evaluation. To address these challenges, future directions are proposed: (1) developing adaptive discretization methods (e.g., MIC, genetic algorithms) and continuous geographical detectors; (2) conducting multi-scale modeling across watershed, county, and national levels; (3) coupling with causal inference frameworks (SEM, Bayesian networks, causal forests); (4) integrating machine learning (random forest, XGBoost, SHAP) and nonlinear models (GAM) to quantify interaction forms; (5) constructing spatiotemporal geographical detectors using multi-temporal remote sensing data; (6) establishing a standardized uncertainty assessment framework based on NUSAP and Monte Carlo simulation; and (7) fusing multi-source big data (Sentinel-2, GEDI, MODIS) with deep learning. These advancements will significantly enhance the scientific value of geographical detectors in soil pollution source tracing, erosion risk early warning, and ecological restoration decision-making, with important implications for soil protection in key regions such as the black soil region of Northeast China and the karst region of South China.

Keywords

Geographical Detector, Soil science, Spatial heterogeneity.

1. Introduction

Soil is an important component of terrestrial ecosystems and a vital natural resource for ensuring food security, maintaining ecological environment stability, and supporting regional sustainable development. Soil physicochemical properties, nutrient status, and pollution characteristics not only affect crop growth and ecosystem functions but are also directly related to land resource utilization efficiency and ecological environmental quality. As soil formation is influenced by the long-term combined effects of climate, topography, parent material, organisms, and human activities, its spatial differentiation exhibits significant heterogeneity and complexity. Deeply revealing the formation mechanisms of soil spatial heterogeneity and quantitatively identifying the contributions of different environmental factors to soil spatial differentiation are fundamental to research in soil survey, digital soil mapping, soil quality assessment, and pollution prevention.

For a long time, related studies have mainly employed methods such as correlation analysis, multiple regression, geostatistics, and spatial regression to analyze the patterns of soil spatial differentiation. These methods have played an important role in revealing the variation characteristics of soil properties, but they mostly focus on linear relationships between variables, with relatively limited capability in depicting multi-factor coupling effects and complex nonlinear spatial heterogeneity. With the rapid development of geographic information systems (GIS), remote sensing, digital elevation models (DEMs), and multi-source environmental data, soil spatial analysis has gradually shifted from descriptive studies to quantitative analysis of driving mechanisms, raising higher demands for analytical methods capable of identifying spatial differentiation patterns and their formation mechanisms.

The Geographical Detector is a statistical analysis method based on the theory of spatial differentiation. Its core idea is that "if an influencing factor plays an important role in the study object, the two should have similar spatial distributions." This method does not require traditional statistical assumptions such as normal distribution, linear relationships, or multicollinearity. It can quantitatively assess the explanatory power of different factors on spatial differentiation and analyze the interaction between factors as well as their enhancement or weakening effects. Therefore, it is particularly suitable for studying the driving mechanisms of complex natural geographical processes.

In recent years, the Geographical Detector has been widely applied in studies of soil organic carbon, nutrient elements, soil salinization, heavy metal pollution, soil quality assessment, and digital soil mapping, providing important technical support for identifying dominant factors of soil spatial differentiation, revealing the coupling effects of environmental factors, and optimizing spatial prediction models. Despite the expanding application of the Geographical Detector in soil science, existing studies still face issues such as scattered application fields, the lack of unified standards for factor discretization schemes, insufficient utilization of different detector functions, and relatively limited integration with machine learning, geostatistics, and other methods. Based on this, this paper systematically reviews the basic principles, main functions, and applications of the Geographical Detector in soil research, as well as the existing problems, and provides an outlook on future development directions, aiming to offer references for further applications of the Geographical Detector in soil science and related research.

2. The Basic Principles and Core Functions

The factor detector of the Geographical Detector is used to detect the explanatory power of X on Y, and the expression is as follows [1]:

$$q = 1 - \sum_{h=1}^{L} \frac{N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{1}$$

$$SSW = \sum_{h=1}^{L} N_h \, \sigma_h^2 \tag{2}$$

$$SST = N\sigma^2 \tag{3}$$

Where h = 1, 2, …, L denotes the strata (i.e., the categories or intervals after discretization) into which the independent variable X is partitioned; Nh and N are the numbers of sample units in the h-th stratum and the entire study area, respectively; σh^2 and σ^2 are the variances of the dependent variable Y within the h-th stratum and the entire region, respectively; SSW is the sum of within-stratum variances; SST is the total regional variance; q is the explanatory power of the independent variable X on the dependent variable Y, where $0 \le q \le 1$, with a larger value indicating stronger explanatory power. The dominant factors causing the spatial differentiation

ISSN: 2710-0588

characteristics of the soil properties can be identified based on the q values. The interaction detector is used to determine the synergistic effects between factors by comparing the q values of single factors and those of two-factor interactions (Table 1).

Table 1. Interaction judgment basis

Description	Interaction type
$q(X_1 \cap X_2) < Min(q(X_1), q(X_2))$	Nonlinear weakening
$Min(q(X_1), q(X_2)) < q(X_1 \cap X_2) < Max(q(X_1), (X_2))$	Single-factor nonlinear weakening
$q(X_1 \cap X_2) < Max(q(X_1), (X_2))$	Two-factor enhancement
$q(X_1 \cap X_2) = q(X_1) + q(X_2)$	Independent
$q(X_1 \cap X_2) > q(X_1) + q(X_2)$	Nonlinear enhancement

The geographical detector, as a statistical analysis method based on spatial heterogeneity theory, has its core functions embodied in four interrelated aspects, each corresponding to different scientific questions.

(1) Factor detection aims to assess the explanatory power of a single influencing factor on the spatial differentiation of the dependent variable. By calculating the ratio of the weighted variance of the dependent variable within each stratum of the factor to the global variance, the q-statistic is obtained. The q-value ranges from 0 to 1; the larger the value, the stronger the control effect of the factor on the dependent variable. Meanwhile, the statistical significance of the q-value can be determined using the Monte Carlo permutation test, thereby distinguishing genuine factor contributions from spurious ones. This function quickly identifies the single dominant driving factor for the target variable within the study area.

(2) Interaction detection is used to reveal whether the joint effect of two factors on the dependent variable differs from the superposition of their individual effects. The method involves calculating the q-values of the two factors acting separately, and then calculating the q-value when the two factors interact (i.e., based on a new classification formed by overlaying the strata of the two factors). By comparing the magnitudes of these three values, the type of interaction can be determined, including five cases: nonlinear weakening, single-factor nonlinear weakening, two-factor enhancement, independent, and nonlinear enhancement. A large number of empirical studies have shown that "two-factor enhancement" and "nonlinear enhancement" are the most common types of interaction, meaning that the synergistic effect between factors is often stronger than the simple sum of their individual effects.

(3) Risk area detection aims to identify spatial subregions where the mean of the dependent variable differs significantly. By performing a t-test or F-test on the means of the dependent variable within different strata of a factor, it is possible to determine which categories (e.g., a certain land use type or a certain slope grade) correspond to dependent variable values that are significantly higher or lower than those of other categories. This function provides a statistical basis for managers to delineate high-risk or low-risk areas, for example, in soil pollution studies to identify regions with the most severe heavy metal accumulation.

(4) Ecological detection is used to compare whether the control effects of two different factors on the spatial distribution of the dependent variable differ significantly. The principle involves testing the differences in within-stratum variances of the two factors using the F-statistic. If the within-stratum variances differ significantly, it indicates that the mechanisms by which the two factors influence the dependent variable are inherently different. This function helps to screen out key environmental factors whose influences are fundamentally distinct.

Together, these four functions constitute the complete analytical framework of the geographical detector, enabling it to systematically analyze the driving mechanisms of multiple

ISSN: 2710-0588

factors on the spatial differentiation of geographical phenomena without the need for linear assumptions.

3. Application of Geographical Detector in Soil Research

Since the geographical detector method was proposed by Wang Jinfeng[2] et al., it has been widely applied in soil science research, with a wealth of empirical cases accumulated both domestically and internationally. Li Yu et al. (2017) used a geographical detector model to quantitatively examine the explanatory power of six factors—including GDP, temperature, and humidity—on the spatial distribution of five soil heavy metals and their interactions, thereby screening key auxiliary variables for spatial prediction models of soil heavy metals[3]. Qiao Pengwei et al. (2019) employed a geographical detector model to quantitatively identify the main influencing factors of soil heavy metal pollution in Huanjiang County and their interactions, and based on factor stratification and interpolation uncertainty analysis, delineated high-risk areas for total and water-soluble heavy metals[4]. Zhao Yinjun et al. (2020) quantitatively analyzed the sources and dominant influencing factors of soil cadmium in both non-mining and mining areas of a high-background cadmium-contaminated region in Guangxi, and subsequently predicted high-risk areas for soil cadmium[5]. Huang Donghao et al. (2024) screened key factors significantly affecting the spatial distribution of gullies in the black soil region of Northeast China from 14 geographic environmental factors, and assessed the risk levels of gully erosion based on these factors[6]. Overall, because the geographical detector is insensitive to linear assumptions and can effectively diagnose synergistic or antagonistic effects among factors, it has become an important tool for studying the mechanisms of soil spatial differentiation.

4. Problems Currently Exist

Although the geographical detector has achieved good results in the aforementioned studies, its application still has several limitations. First, the method is sensitive to the discretization of continuous variables. The geographical detector requires that the input independent variables be categorical variables or continuous variables after discretization. Different discretization strategies (e.g., equal interval, quantile, natural breaks) and the choice of the number of strata can significantly affect the calculated q-values. Second, constraints related to sample size and spatial scale cannot be overlooked. The geographical detector requires a sufficient sample size to maintain statistical stability. If the sampling points are unevenly distributed or the sample size is too small, some factors may be incorrectly judged as insignificant due to a lack of spatial representativeness. Furthermore, the geographical detector is highly dependent on the spatial scale of environmental factors; the same factor may exhibit markedly different explanatory power at different scales, yet scale selection in most studies lacks sufficient justification. Meanwhile, existing research is mostly based on spatial analysis at a single time snapshot, lacking temporal dynamic analysis, making it difficult to reveal the variation patterns of soil pollution or erosion processes over time.

5. Conclusions and Prospects

Currently, geographic detectors have been widely applied in the identification of soil heavy metal pollution and the assessment of soil erosion risk. However, they still have limitations in terms of discretization sensitivity, scale dependence, causal inference, analysis of interaction mechanisms, capturing temporal dynamics, and uncertainty assessment. Future research can achieve breakthroughs in the following directions:

(1) Developing adaptive discretization and continuous geographic detectors

ISSN: 2710-0588

To address the instability of discretizing continuous variables, future work can explore data-driven optimal discretization methods. For example, using the maximum information coefficient (MIC) or genetic algorithms to automatically optimize the number of strata and breakpoint positions, thereby making the q-statistic calculation more robust.

(2) Introducing multi-scale and spatial representativeness optimization strategies

Geographic detectors are highly sensitive to spatial scale. Future research should systematically conduct multi-scale analyses: repeat modeling at watershed, county, provincial, and even national scales to reveal the scale dependence of factor contributions.

(3) Strengthening causal inference: Integrating structural equation models and counterfactual frameworks

Geographic detectors are essentially tools for correlation analysis and cannot directly reveal causal mechanisms. In the future, they can be coupled with structural equation models (SEM), Bayesian networks, or causal forests.

(4) Deepening interaction mechanism analysis: Introducing machine learning and nonlinear modeling

Existing interaction detectors only output relationships of enhancement or weakening, lacking a quantitative description of the interaction form. Future work can leverage feature interaction importance (e.g., SHAP interaction values) from machine learning models such as random forest and XGBoost, or smooth terms from generalized additive models (GAM), to quantitatively characterize nonlinear synergistic or antagonistic effects between factors.

(5) Constructing spatiotemporal geographic detectors to enable dynamic process analysis

Current studies are mainly based on static cross-sectional data, failing to reflect the processual characteristics of pollution or erosion. Future research should develop spatiotemporal geographic detectors: use multi-temporal remote sensing data (e.g., Landsat images from the 1980s, 2000s, and 2020s) to extract changes in gullies or heavy metals as dependent variables, introduce temporal variables as new dimensions, and analyze the temporal evolution of factor contributions.

(6) Establishing a standardized uncertainty assessment framework

Current studies lack systematic evaluation of data errors, discretization errors, and model structure errors. In the future, a guideline for uncertainty analysis in geographic detector applications should be developed, following the NUSAP (Numeral, Unit, Spread, Assessment, Pedigree) method. Specific steps include: (1) using Monte Carlo simulations or Bayesian inference to quantify the impact of input data (e.g., DEM accuracy, LULC classification errors) on the q-statistic; (2) employing moving-window spatial bootstrapping to assess the stability of sample spatial configurations; (3) reporting confidence intervals and sensitivity intervals of the q-statistic.

(7) Promoting the integration of multi-source big data and artificial intelligence

With the proliferation of remote sensing, drones, and IoT sensors, geographic detectors in the future can process higher-dimensional and more detailed environmental variables. For example, using Sentinel-2 10-meter resolution vegetation indices, GEDI LiDAR topographic data, and MODIS time-series products to construct multi-scale factor sets including vegetation phenology, micro-topography, and soil moisture dynamics. Meanwhile, integrating with deep learning methods (e.g., convolutional neural networks, graph neural networks) to automatically extract spatial differentiation patterns of high-dimensional features, which are then interpreted using geographic detectors, forming a closed loop of "data-driven to mechanism interpretation."

In summary, the application of geographic detectors in soil environmental research is evolving from univariate static correlation analysis to multi-scale dynamic causal inference. The core of

ISSN: 2710-0588

future directions lies in: improving the method's dependence on discretization and scale, introducing causal inference frameworks to overcome correlation limitations, developing spatiotemporal modeling and uncertainty quantification systems, and integrating multi-source remote sensing and AI technologies. These breakthroughs will significantly enhance the scientific value of geographic detectors in soil pollution source tracing, erosion risk early warning, and ecological restoration decision-making. This is of particular practical importance for soil protection and sustainable utilization in key regions such as the black soil region of Northeast China and the karst region of South China.

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