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Mengyao Jia

Huazhong Agricultural University

Yong Yang

yangyong@mail.hzau.edu.cn

Huazhong Agricultural University

Pengguang Guo

Huazhong Agricultural University

Yuzhi Zhou

Zigui Agricultural Science and Technology Service Center

Chen Cai

Zigui Agricultural Science and Technology Service Center

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Spatiotemporal Evolution and Uncertainty Analysis of Soil Acidification at the County Scale

Mengyao Jia^{a,b,c}, Yong Yang^{a,b,c*}, Pengguang Guo^a, Yuzhi Zhou^d, Chen Cai^d

^aCollege of Resources and Environment, Huazhong Agricultural University, Wuhan, 430070, China

^bHubei Key Laboratory of Soil Environment and Pollution Remediation

^cKey Laboratory of Arable Land Conservation (Middle and Lower Reaches of Yangtze River), Ministry of Agriculture, China

^dZigui Agricultural Science and Technology Service Center, Yichang, 443600, China

* Corresponding authors: Yong Yang

Email: yangyong@mail.hzau.edu.cn

Abstract: Soil acidification is one of the most critical forms of soil degradation worldwide; however, its spatial uncertainty, based on continuous spatiotemporal datasets, remains insufficiently characterized. In this study, Zigui County, a typical citrus- and tea-producing region in China, was selected as the study area. Based on soil pH monitoring data collected from cultivated land and orchards between 2006 and 2024, a continuous soil pH dataset was reconstructed using spatiotemporal kriging. Subsequently, soil Δ pH was analyzed using the Stochastic Site Indicators (SSI) method to systematically quantify the occurrence probability, variation intensity, and spatial uncertainty of soil acidification under different threshold conditions. Results showed that soil pH in cultivated land and orchards generally exhibited a decreasing trend from 2006 to 2024, with a cumulative decline of 0.24 pH units; however, the temporal trajectory was characterized by an initial decline, followed by a recovery and a subsequent decrease. Single-point SSI analysis indicated that 6%, 22%, and 17% of the study area experienced severe, moderate, and slight soil acidification, respectively. Two-point SSI analysis further revealed the spatial dependence and scale effects of soil acidification events under different threshold conditions, enabling a quantitative assessment of their spatial uncertainty. Through the integration of spatiotemporal kriging with the SSI method, this study establishes a framework for analyzing the spatial uncertainty of soil acidification, providing

a scientific basis for regional soil acidification risk assessment, precision management, and the optimization of agricultural management practices.

Keywords: Soil acidification; Stochastic Site Indicators (SSI); Spatiotemporal kriging; Uncertainty

1. Introduction

Soil acidification is one of the major environmental challenges affecting agricultural ecosystems worldwide and is a key constraint on cultivated land quality and sustainable agricultural development (Goulding, 2016; Xu et al., 2025). Over recent decades, the combined effects of acid deposition (e.g., SO₂ and NH₃ emissions), long-term fertilizer application, and intensive agricultural activities have accelerated soil acidification in the croplands of southern China, posing a major threat to sustainable agricultural production (Chen et al., 2022; L. Zhang et al., 2024; Zou et al., 2025). Therefore, accurately characterizing the spatiotemporal evolution and spatial heterogeneity of soil acidification is of considerable importance for regional soil quality assessment, agroecosystem protection, and precision soil management.

A continuous decline in soil pH not only reduces nutrient availability and soil buffering capacity but also accelerates the leaching of base cations (e.g., Ca²⁺ and Mg²⁺), increases aluminum (Al) saturation, and consequently leads to crop yield reduction and soil structure deterioration (Du et al., 2024; Wang et al., 2024; Robles-Aguilar et al., 2019). Moreover, soil pH exhibits strong spatiotemporal dependence, with its status at a given time is strongly influenced by previous conditions (Xie et al., 2019; Xu et al., 2020). Previous existing studies have investigated the spatiotemporal evolution of soil acidification by directly analyzing multi-temporal point observations or reconstructing soil pH distributions for individual monitoring periods using conventional geostatistical methods, such as ordinary kriging, or machine learning approaches, including random forests (Kaae et al., 2022; J. H. Guo et al., 2010; Lapenis et al., 2004; Y. Zhang et al., 2024; Xie et al., 2019; Sun et al., 2003; Zhang et al., 2025; Zhenfu Wu et al., 2022). Regardless of the analytical strategy employed, observations from different monitoring periods are generally treated as independent datasets, with limited consideration of the spatiotemporal dependence among consecutive observations. In contrast, spatiotemporal kriging explicitly incorporates spatial and temporal correlation structures, enabling the joint prediction of soil pH by fully leveraging the

spatiotemporal dependence inherent in multi-temporal monitoring data. This strategy helps improve the accuracy of long-term soil pH reconstruction and dynamic change analysis, establishing a highly reliable basis for investigating the spatiotemporal evolution of regional soil acidification (S. Li et al., 2024).

Meanwhile, existing studies have mainly considered soil pH and its changes as continuous variables, focusing on the spatial distribution and temporal evolution of soil acidification while providing minimal attention to its associated spatial uncertainty (Goovaerts, 1999). However, soil acidification is inherently a continuous process characterized by its threshold-dependent behavior, and the delineation of acidified areas largely depends on the selected threshold (Slessarev et al., 2016). Variations in threshold values may substantially alter the spatial extent, aggregation pattern, and spatial dependence of acidified regions (Lebron et al., 2025). Despite the effectiveness of conventional geostatistical methods in mapping the distribution of soil acidification, they cannot fully characterize its spatial uncertainty. Specifically, they are inadequate for quantifying the probability of acidification under different threshold conditions, the joint occurrence probability of acidification at multiple locations, and the associated spatial continuity. In particular, these methods fail to characterize the spatial evolution of soil acidification, accurately identify areas with varying levels of acidification risks, or provide a scientific basis for developing spatially targeted soil improvement measures, thereby reducing the efficiency of soil amendment resource allocation. These limitations may also compromise the effectiveness of site-specific fertilization and soil management practices while increasing the uncertainty of regional agricultural management decisions. Therefore, quantifying the spatial uncertainty of soil acidification from a probabilistic perspective under different threshold conditions remains a crucial challenge in regional soil acidification research.

Stochastic Site Indicators (SSI) provide an effective approach for characterizing the spatial uncertainty of environmental variables. Through the transformation of continuous environmental variables into threshold-defined binary events, SSI enables the quantification of exceedance probabilities above or below specified critical thresholds while characterizing spatial heterogeneity. The theoretical foundation of this approach originates from the indicator geostatistical framework (Journel, 1983). Building on this foundation, Christakos and Hristopulos extended the stochastic indicator modeling framework within the Bayesian Maximum Entropy theory, further improving

the representation of spatial uncertainty in complex contaminated environments (Christakos and Hristopulos, 1997, 1996a, 1996b). To date, indicator-based stochastic modeling approaches have been extensively applied in environmental pollution risk assessment and groundwater quality analysis, particularly for probabilistic mapping of contaminant exceedance and the visualization of spatial uncertainty (Chang and Jang, 2026; He et al., 2019; Yang and Christakos, 2015; Sheikhy Narany et al., 2014; Lin et al., 2010). However, the application of these methods to soil acidification studies remains limited, and their potential for characterizing threshold-dependent responses and quantifying spatial uncertainty in soil acidification has not yet been fully explored. Therefore, further investigation is necessary to evaluate their applicability and potential in the spatial uncertainty analysis of soil acidification.

Accordingly, this study used soil pH monitoring data collected from cultivated land and orchards in Zigui County between 2006 and 2024 to construct a long-term continuous soil pH dataset using spatiotemporal kriging. Based on variations in soil pH (ΔpH), a single-point and two-point SSI framework was established to systematically investigate the occurrence probability, variation intensity, spatial dependence, and spatial uncertainty of soil acidification under different threshold conditions. The findings are expected to improve the understanding of the spatial structure and scale effects of soil acidification while establishing a new analytical framework for assessing spatial uncertainty, identifying risk areas, and supporting precision management of regional soil acidification.

2. Materials and Methods

2.1 Study area and soil data

The study area is located in Zigui County, Yichang City, Hubei Province, China, along the Xiling Gorge of the Yangtze River and at the head of the Three Gorges Reservoir region. As a typical mountainous area within the Three Gorges Reservoir region, Zigui features complex terrain dominated by mountains and hills, with widely distributed sloping land. Consequently, agricultural activities in this region are primarily conducted on sloping farmland. The major land-use types include orchards, dry farmland, and forest land, leading to the formation of a fragmented land-use structure.

Zigui has a subtropical monsoon climate characterized by mild and humid conditions and abundant precipitation, which is favorable for agricultural production. The region is particularly suitable for the cultivation of cash crops, such as citrus and tea, and is widely known as the “Hometown of Chinese Navel Oranges” and the “Hometown of Silk Cotton Tea.” The advancement of citrus and tea cultivation, along with associated fertilization and management practices, has substantially influenced soil pH dynamics (Chen et al., 2025; Zhang et al., 2023). As an important part of the Three Gorges Reservoir region, Zigui has been strongly affected by the impoundment of the Three Gorges Project. The formation of a typical water-level fluctuation zone, along with pronounced seasonal water-level variations, has further influenced soil physicochemical properties, vegetation distribution, and land-use patterns in the region, thereby affecting soil pH variations.

A total of 15,799 soil samples collected between 2006 and 2024 were used in this study. Among these samples, data collected from 2006 to 2023 were obtained from the *Soil Testing and Formulated Fertilization Program*, a nationwide soil fertility monitoring program in China. However, these sampling locations did not provide complete spatial coverage of all cultivated land and orchard areas. Therefore, interpolation based solely on single-year observations could not produce continuous soil pH datasets for the entire study area. The 2024 soil samples were collected by conducting independent field sampling. Sampling sites were then established based on historical sampling locations and distributed across cultivated land and orchards according to a random and uniform sampling principle.

All soil samples were collected from the topsoil layer (0–20 cm). At each sampling site, multiple subsamples were collected using a grid-based sampling method and thoroughly mixed to form a composite sample. After removal of stones, plant residues, and other debris, approximately 1 kg of soil was retained using the quartering method. The soil samples were then air-dried at room temperature, ground, and sieved prior to analysis. Soil suspensions were prepared at a soil-to-water ratio of 1:2.5 (w/v), and soil pH was measured using a pH meter equipped with glass and calomel electrodes acting as the indicator and reference electrodes, respectively.

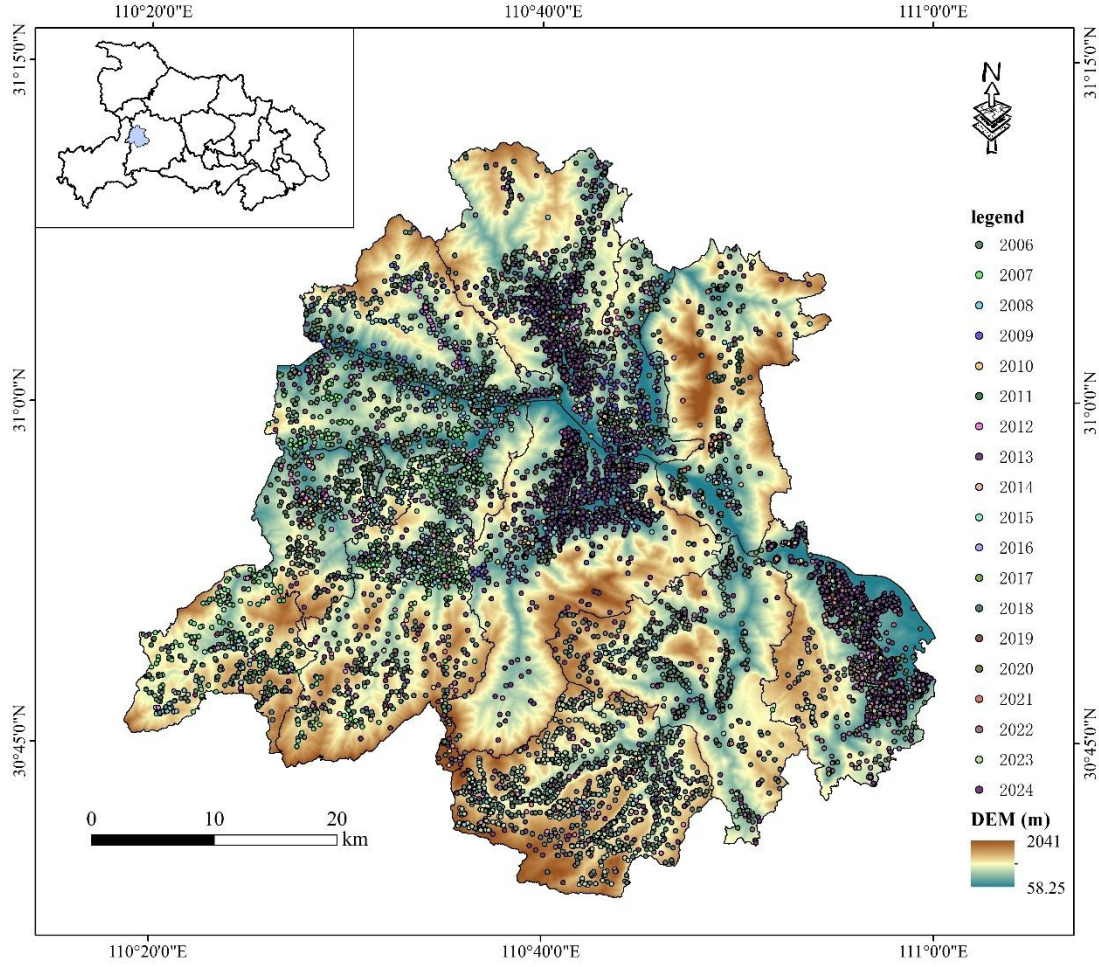


Figure 1. Location of the study area and spatial distribution of sampling sites

2.2 Spatiotemporal kriging interpolation

2.2.1 Spatiotemporal variogram model

Soil pH can be regarded as a spatiotemporal random field that varies across location and time, thereby reflecting its spatiotemporal variability within the study area. Accordingly, a spatiotemporal experimental variogram (Equation 1) can be constructed by extending the two-dimensional experimental variogram. Subsequently, a theoretical variogram can be fitted to the spatiotemporal experimental variogram (Equation 2).

$$\gamma(h_s, h_t) = \frac{1}{2N(h_s, h_t)} \sum_{i=1}^{N(h_s, h_t)} [z(s, t) - z(s + h_s, t + h_t)]^2, \quad (1)$$

$$\gamma(h_s, h_t) = c_0 + c_1 \left(1 - \exp\left(-\frac{h_s}{a_1}\right)\right) + c_2 \left(\frac{3h_t}{2a_2} - \frac{h_t^2}{2a_2^3}\right), \quad (2)$$

where s denotes the spatial location; t indicates the sampling time; h_s and h_t represent spatial and temporal lags, respectively; and $N(h_s, h_t)$ denotes the number of point pairs with a

spatiotemporal lag of (h_s, h_t) among all sampling points. c_0 represents the nugget value, while $c_0 + c_1 + c_2$ denotes the sill value. Parameters a_1 and a_2 are associated with the spatial and temporal ranges, respectively.

The attribute value at an unsampled location, $p_0 = (s_0, t_0)$, can be estimated as a weighted sum of the values from n neighboring soil samples.

$$z(p_0) = \sum_{i=1}^n \lambda_i z(p_i), \quad (3)$$

where λ_i denotes the weight assigned to the i -th neighboring soil sample p_i . All weights are identified using the kriging system matrix (Equation 4).

$$\begin{cases} \begin{bmatrix} \gamma_{11} & \gamma_{12} & \cdots & \gamma_{1n} & 1 \\ \gamma_{21} & \gamma_{22} & \cdots & \gamma_{2n} & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \gamma_{n1} & \gamma_{n2} & \cdots & \gamma_{nn} & 1 \\ 1 & 1 & \cdots & 1 & 0 \end{bmatrix} \times \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} = \begin{bmatrix} \gamma_{10} \\ \gamma_{20} \\ \vdots \\ \gamma_{n0} \\ 1 \end{bmatrix} \\ \gamma_{ij} = \gamma(p_i, p_j) = \gamma(h_{s_{ij}}, h_{t_{ij}}) \end{cases} \quad (4)$$

In the above equation, the theoretical spatiotemporal variogram value between the i -th and j -th samples depends on the spatial distance $h_{s_{ij}}$ and temporal distance $h_{t_{ij}}$ between the two points. Additionally, the kriging estimation variance at this location can be calculated (Equation 5).

$$\sigma^2 = \sum_{i=1}^n \lambda_i \gamma(\mathbf{p}_i, \mathbf{p}_0) - \gamma(\mathbf{p}_0, \mathbf{p}_0) + \mu. \quad (5)$$

2.2.2 Accuracy assessment

Aiming to evaluate the accuracy of the spatiotemporal kriging interpolation, 80% of the soil samples from each year were randomly selected as the training set, while the remaining 20% were allocated for validation. Interpolation accuracy was measured using the coefficient of determination (R^2), root mean square error ($RMSE$), and mean absolute error (MAE), providing an assessment of the reliability and precision of the predicted values.

$$R^2 = 1 - \frac{\sum (z(p_i) - \hat{z}(p_i))^2}{\sum (z(p_i) - \bar{z}(p_i))^2}, \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n [z(p_i) - \hat{z}(p_i)]^2}, \quad (7)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |z(p_i) - \hat{z}(p_i)|, \quad (8)$$

where n is the number of validation samples, $z(p_i)$ denotes the observed soil pH value at the spatiotemporal location p_i , $\hat{z}(p_i)$ represents the predicted soil pH value at the same location, and

$\bar{z}(p_i)$ denotes the mean of the observed soil pH values. Lower *RMSE* and *MAE* values indicate higher prediction accuracy, whereas an R^2 value closer to 1 reflects stronger agreement between the observed and predicted values.

2.3 Mann–Kendall (MK) trend test

Aiming to quantitatively evaluate the temporal trend of soil pH from 2006 to 2024, the Mann–Kendall (MK) trend test was applied to the soil pH time series at each spatial location. For a time series with a length of n , the MK test statistic S is defined as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(t_j - t_i), \quad (9)$$

where t_i and t_j represent the soil pH values in the i -th and j -th years of the time series, respectively, with $1 \leq i < j \leq n$; n represents the length of the time series, which was set to 19 in this study; and sgn as defined in Equation (10).

$$\text{sgn} = \begin{cases} 1 & \theta > 0 \\ 0 & \theta = 0 \\ -1 & \theta < 0 \end{cases}. \quad (10)$$

The standardized statistic, Z , was calculated using Equation (11) to assess the significance of the trend. Absolute values exceeding 1.65, 1.96, and 2.58 correspond to significance levels of 90%, 95%, and 99%, respectively. Meanwhile, the magnitude of the trend was quantified using Sen's slope (β), as expressed in Equation (12), where positive and negative values indicate increasing and decreasing trends, respectively. The variance of S is given by $\text{Var}(S) = \frac{n(n-1)(n+5)}{18}$, where Median denotes the median of the time series.

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases}, \quad (11)$$

$$\beta = \text{Median}\left(\frac{x_j - x_i}{j - i}\right). \quad (12)$$

2.4 Stochastic site indicators

In this study, soil pH change (ΔpH) during 2006–2024 was calculated as the difference between the interpolated soil pH values in 2024 and those in 2006 ($\Delta\text{pH} = \text{pH}_{2024} - \text{pH}_{2006}$). Based on ΔpH , the spatial patterns of soil acidification were characterized through indicator transformation under

varying threshold levels, with the aim of investigating acidification processes in Zigui County. Let $\Delta\text{pH}(s)$ denote a spatial random field defined over domain D . For a given threshold ζ , the indicator transformation is defined as follows:

$$I(s; \zeta) = \begin{cases} 1, & \text{if } \Delta\text{pH}(s) \leq \zeta \\ 0, & \text{otherwise} \end{cases} \quad (13)$$

where ζ is a threshold within the range $[\Delta\text{pH}_{\min}, \Delta\text{pH}_{\max}]$. The spatial variable $\Delta\text{pH}(s)$ was transformed into a binary indicator random field through thresholding $I(s; \zeta)$. The indicator field represents the spatial occurrence of acidification exceedance while ensuring the spatial dependence structure of the original variable. $\Delta\text{pH}(s)$ and its corresponding indicator function $I(s; \zeta)$ jointly form a spatial random function pair $\{\Delta\text{pH}(s), I(s; \zeta)\}$, which enables the characterization of the spatial continuity and connectivity of soil acidification processes across different threshold levels.

2.4.1 Single-point SSI

Within the SSI framework, a series of single-point indicators was applied to characterize the distribution and uncertainty of values below a given threshold within the spatial domain. The corresponding formulas and definitions of these indicators are summarized in Table 1. The relative area below threshold (RABT, $R_{\Delta\text{pH}}(\zeta)$) is a monotonically increasing function of the threshold ζ . In this study, ζ was constrained within the interval defined by the minimum and maximum values of the continuously distributed ΔpH dataset, such that $R_{\Delta\text{pH}}(\zeta_{\min}) = 0$ and $R_{\Delta\text{pH}}(\zeta_{\max}) = 1$. The mean below threshold (MBT, $P_{\Delta\text{pH}}^D(\zeta)$) represents the mean value of soil ΔpH below the threshold across the entire study domain D . The mean differential below threshold (MDBT, $L_{\Delta\text{pH}}^D(\zeta)$) calculates the average difference between the threshold ζ and the ΔpH values below this threshold over the entire spatial domain D . The conditional mean below threshold (CMBT, $P_{\Delta\text{pH}}^\Theta(\zeta)$) is the mean value of ΔpH below the threshold ζ within the sub-region Θ , where $\Theta = \{s \in D | \Delta\text{pH} < \zeta\}$. The below-threshold odds (BEO, $O_{\Delta\text{pH}}(\zeta)$) represent the ratio of the area below the threshold to that above the threshold. In site indicator elasticity (SIE, $E_K(\zeta)$), K represents the set of single-point indicators defined above. SIE measures the sensitivity of each indicator to a 1% perturbation in the threshold, thereby describing their responsiveness to threshold variations.

Table 1 Single-point stochastic site indicators

Single-point SSI	Equation ($s = (s_1, s_2)$)	Interpretation
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Relative Area Below Threshold (RABT)	$R_{\Delta pH}(\zeta) = I_{\Delta pH}(s, \zeta)$	Relative area below the threshold
Mean Below Threshold (MBT)	$P_{\Delta pH}^D(\zeta) = \overline{\Delta pH(s)I_{\Delta pH}(s, \zeta)}$	Mean ΔpH below the threshold across the entire spatiotemporal domain
Mean Differential Below Threshold (MDBT)	$L_{\Delta pH}^D(\zeta) = \overline{[\zeta - \Delta pH(s)]I_{\Delta pH}(s, \zeta)}$	Mean difference between ΔpH and the threshold below the threshold across the entire spatiotemporal domain
Conditional Mean Below Threshold (CMBT)	$P_{\Delta pH}^\Theta(\zeta) = \overline{\Delta pH(s) \Delta pH(s) \leq \zeta}$	Mean value below the threshold
Below-Threshold Odds (BTO)	$O_{\Delta pH}(\zeta) = R_{\Delta pH}(\zeta)/(1 - R_{\Delta pH}(\zeta))$	Ratio of the area below the threshold to that above the threshold
Site Indicator Elasticity (SIE)	$E_K(\zeta) = \frac{dK_{\Delta pH}(\zeta)}{K_{\Delta pH}(\zeta)} / \frac{d\zeta}{\zeta}$	Measure of the elasticity (sensitivity) of indicators to threshold variation

240

241 2.4.2 Two-point SSI

242 In addition to the single-point SSI, a series of two-point SSIs was employed to further
243 characterize the spatial relationships and uncertainty levels. Table 2 presents the corresponding
244 formulations and definitions of these indicators. The non-centered indicator covariance (NIC,
245 $c_I(\delta_s; \zeta)$), a bivariate spatial indicator, is a function of the spatial lag δ_s . Conceptually, NIC
246 characterizes the spatial dependence of ΔpH values below the threshold ζ . Specifically, this
247 indicator quantifies the joint dependence between ΔpH values at two spatial locations, s and s' ,
248 separated by a lag distance δ_s , where both values are below ζ . The centered indicator covariance
249 (CIC, $\tilde{c}_I(\delta_s; \zeta)$) is defined as a function of RABT and NIC and is used to characterize the spatial
250 fluctuations of ΔpH around RABT under different threshold conditions. The non-centered below-
251 threshold covariance (NBC, $P_{\Delta pH}^D(\delta_s; \zeta)$) measures the spatial association between two locations

under threshold conditions, where ΔpH values at both locations are below the specified threshold ζ and separated by a spatial lag δ_s . The differential below-threshold covariance (DBC, $L_{\Delta\text{pH}}^D(\delta_s; \zeta)$) characterizes the spatial correlation of the below-threshold component of ΔpH . The conditional below-threshold covariance (CBC, $P_{\Delta\text{pH}}^0(\delta_s; \zeta)$) characterizes the spatial dependence structure of ΔpH at lag distance δ_s within the subset constrained by $\Delta\text{pH} < \zeta$. The interaction ratio (IR, $G_{\Delta\text{pH}}(\delta_s; \zeta)$) represents the ratio between the joint probability that ΔpH values at both locations are below ζ and the probability that at least one of the two locations falls below ζ at a given spatial lag δ_s .

Table 2 Two-point stochastic site indicators

Two-point SSI	Equation ($\delta_s = s' - s$)	Interpretation
Non-centered indicator covariance (NIC)	$c_I(\delta_s; \zeta) = \overline{I_{\Delta\text{pH}}(s, \zeta) I_{\Delta\text{pH}}(s', \zeta)}$	Spatial correlation between ΔpH values below the threshold ζ at distance δ_s .
Centered indicator covariance (CIC)	$\tilde{c}_I(\delta_s; \zeta) = c_I(\delta_s; \zeta) - R_{\Delta\text{pH}}^2(\zeta)$	Spatial correlation fluctuations of below-threshold ΔpH variations around RABT.
Non-centered Below-Threshold Covariance (NBC)	$P_{\Delta\text{pH}}^D(\delta_s; \zeta) = \overline{\Delta\text{pH}(s) \Delta\text{pH}(s') I_{\Delta\text{pH}}(s, \zeta) I_{\Delta\text{pH}}(s', \zeta)}$	Spatial connectivity between locations with ΔpH values below the threshold ζ at separation distance δ_s .
Differential Below-Threshold Covariance (DBC)	$L_{\Delta\text{pH}}^D(\delta_s; \zeta) = \overline{[\zeta - \Delta\text{pH}(s)][\zeta - \Delta\text{pH}(s')] I_{\Delta\text{pH}}(s, \zeta) I_{\Delta\text{pH}}(s', \zeta)}$	Spatial correlation of ΔpH variations between two locations with different acidification levels separated by a distance δ_s .
Conditional Below-Threshold Covariance (CBC)	$P_{\Delta\text{pH}}^0(\delta_s; \zeta) = \overline{\Delta\text{pH}(s) \Delta\text{pH}(s') \Delta\text{pH}(s), \Delta\text{pH}(s') \leq \zeta}$	Conditional spatial correlation of ΔpH variations below the threshold ζ at a separation distance δ_s .

Interaction Ratio (IR)	$G_{\Delta pH}(\delta_s; \zeta) = c_I(\delta_s; \zeta) / (2R_{\Delta pH}(\zeta) - c_I(\delta_s; \zeta))$	Ratio of the spatial correlation between ΔpH variations below the threshold ζ at a separation distance δ_s to the overall spatial correlation among all ΔpH variations.
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3 Results and discussion

3.1 Descriptive statistical analysis

Table 3 shows that the soil pH values in the study area ranged from 3.89 to 8.22, with a mean value of 5.97 and a median of 5.86, indicating that the soils were generally weakly acidic. The standard deviation was 1.08, and the coefficient of variation was 0.18, implying a moderate level of soil pH variability. The kurtosis coefficient was 0.26, which is close to zero, indicating that the distribution was approximately normal.

From a temporal perspective, the annual mean values of soil pH demonstrated certain fluctuations over time. The highest and lowest mean values were observed in 2013 (6.51) and 2014 (5.30), respectively. The remarkably high mean value in 2013 may be attributed to the spatial distribution characteristics of the sampling sites. Although the number of samples in that year was the largest among all survey years, most sampling sites were concentrated in only four towns (Guojiaba, Shuitianba, Guizhou, and Maoping), with relatively short distances between adjacent sites (approximately 3 m), resulting in oversampling of local areas. Such spatial clustering may have intensified the influence of local soil properties and agricultural management practices on the annual mean value, thereby reducing its spatial representativeness for that year. In contrast, the relatively low mean pH value in 2014 may be associated with the concentration of sampling sites in Maoping Town, where tea cultivation is dominant. Long-term tea cultivation may promote soil acidification, potentially contributing to the maintenance of relatively low soil pH levels. Additionally, the limited number of samples collected in 2014 may have further reduced the representativeness of the estimated annual mean soil pH. In terms of variability, the coefficient of variation ranged from 0.11 to 0.21 across different years, indicating moderate variability. The lowest coefficient of variation was observed in 2011 (0.11), implying relatively low spatial variability in soil pH during that year.

In contrast, higher coefficients of variation were observed in 2007, 2020, and 2024 (0.21), indicating relatively greater spatial variability during those years.

Table 3 Descriptive statistics of soil pH from 2006 to 2024 based on soil samples.

Year	Count	Min	Max	Mean	Median	Std	CV	Skewness	Kurtosis
2006	2994	3.40	8.70	6.30	6.30	1.12	0.18	−0.93	0.09
2007	837	3.80	8.40	5.94	5.80	1.23	0.21	−1.25	0.20
2008	985	3.40	7.80	5.88	5.90	1.04	0.18	−1.16	−0.09
2009	198	3.40	7.80	5.90	5.85	1.05	0.18	−0.97	0.01
2010	332	3.80	7.40	5.53	5.60	0.72	0.13	−0.59	−0.02
2011	582	4.00	7.30	5.76	5.80	0.64	0.11	−0.25	−0.11
2012	449	4.00	8.40	6.12	6.00	1.20	0.20	−1.16	0.23
2013	5225	3.60	8.90	6.51	6.50	1.32	0.20	−1.33	−0.09
2014	20	4.20	7.00	5.30	5.15	0.89	0.17	−0.72	0.68
2015	205	4.20	8.20	5.95	5.80	1.01	0.17	−0.89	0.41
2016	11	4.70	8.00	5.88	5.60	1.02	0.17	0.44	1.04
2017	71	4.35	8.46	6.18	6.24	1.16	0.19	−0.99	0.33
2018	297	4.53	8.64	6.41	6.20	1.09	0.17	−1.21	0.21
2019	297	3.84	8.61	6.09	6.06	1.24	0.20	−1.32	0.07
2020	417	3.70	8.50	6.07	5.80	1.27	0.21	−1.28	0.25
2021	329	3.61	8.37	6.16	6.13	1.18	0.19	−1.09	−0.03
2022	855	3.60	8.55	5.83	5.60	1.05	0.18	−0.58	0.56
2023	626	3.80	8.50	5.88	5.70	1.13	0.19	−0.90	0.43
2024	1069	4.01	8.60	5.77	5.31	1.22	0.21	−0.76	0.74
Total	15799	3.89	8.22	5.97	5.86	1.08	0.18	−0.89	0.26

Note: Count: the count of soil samples, Min: minimum, Max: maximum, Std: standard deviation, CV: coefficient of variation.

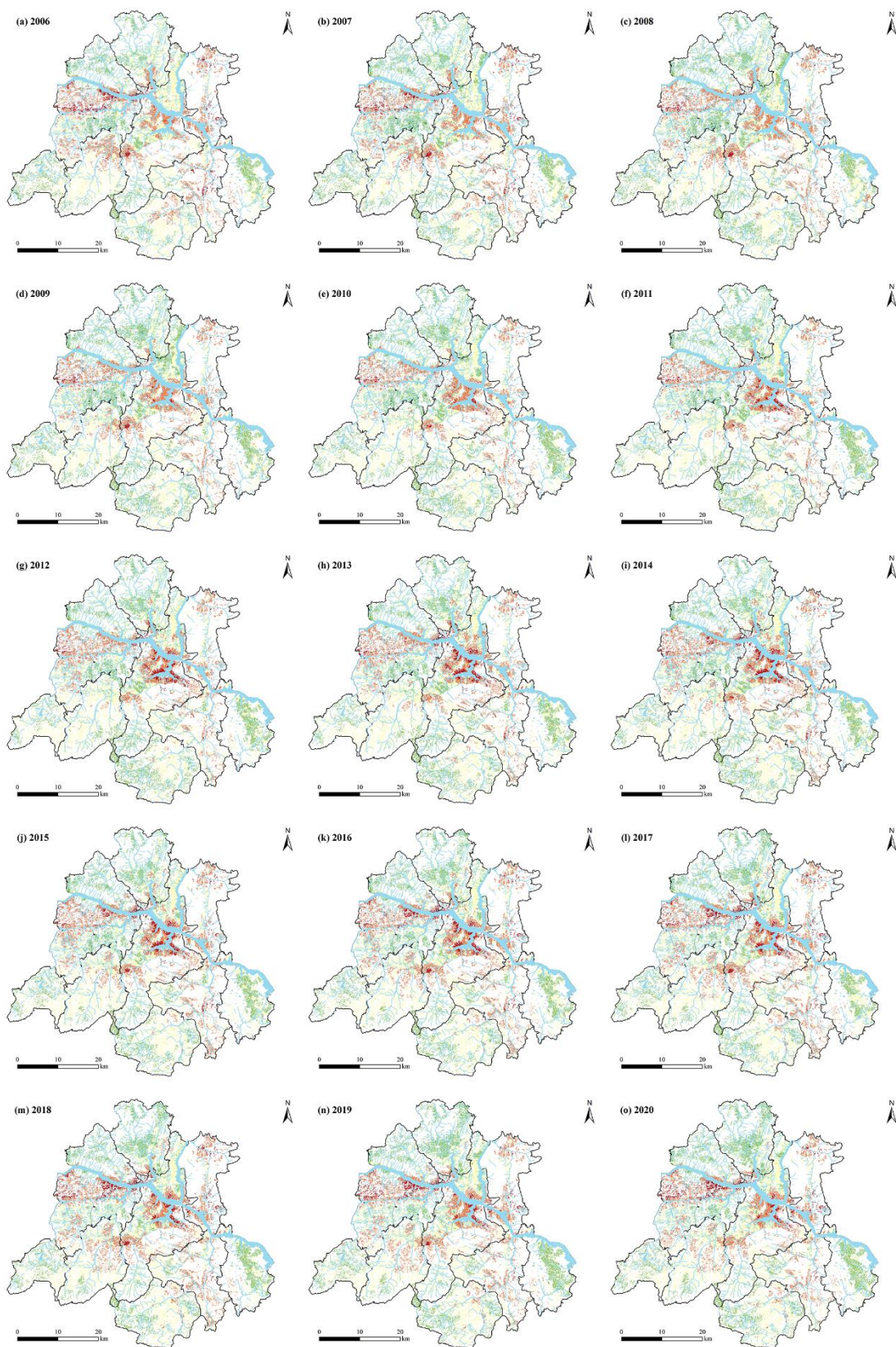
3.2 Spatiotemporal kriging interpolation

According to Equation 1, a spatial lag interval of 500 m and a temporal lag interval of 1 year were adopted to calculate the experimental spatiotemporal variogram values under different spatiotemporal lag conditions. Subsequently, the experimental variogram was fitted using the least squares method based on Equation 2 to establish a theoretical spatiotemporal variogram model. Figure 2(t) shows the fitting results. The fitted theoretical variogram model was used to construct the kriging system, which was applied to perform spatiotemporal kriging interpolation of soil pH across the study area. Table 4 presents the interpolation accuracy. The overall R^2 was 0.54 (> 0.5), indicating that the interpolation model effectively captured the spatial distribution of soil pH in the study area, revealing reliable results. However, the negative ($R^2 = -0.27$) value obtained in 2016 was likely due to the limited number of samples and their uneven spatial distribution. Only 11 samples were available in 2016, of which only three were included in the validation set. The extremely small number of validation samples possibly amplified the influence of individual prediction errors on the assessment of model accuracy. Additionally, compared with 2014, which also had a relatively small number of samples but achieved the highest interpolation accuracy ($R^2 = 0.90$) with 20 samples, the sampling sites in 2016 were mainly concentrated within two small areas in Shuitianba Town. This concentration resulted in limited spatial coverage and insufficient sample representativeness. In contrast, the sampling sites in 2014 were more evenly distributed within Maoping Town, providing better local-scale spatial representativeness, leading to more stable accuracy evaluation of the interpolation results for that year.

Figure 2 presents the spatial distribution, revealing cropland and orchards with a patchy distribution pattern in Zigui County. The soils in the study area were predominantly acidic, possible due to the long-term cultivation of citrus and tea, as well as the corresponding fertilization and management practices (Guo et al., 2025; Zhenyu Wu et al., 2022). In contrast, neutral and alkaline soils were mainly distributed along the Yangtze River and major river corridors, thereby forming distinct belt-like patterns. This distribution may be attributed to alluvial deposition, the enrichment of base cations, and the accumulation of materials in low-lying areas (El Hourani and Broll, 2021; Stutter et al., 2003). Furthermore, areas adjacent to rivers are strongly affected by water-level fluctuations in the Three Gorges Reservoir. The periodic inundation and exposure processes may facilitate the migration and accumulation of alkaline ions, thereby maintaining relatively high soil pH values (X. Li et al., 2024; Shen et al., 2022).

Table 4. Accuracy assessment of spatiotemporal kriging interpolation.

Year	R^2	$RMSE$	MAE
2006	0.46	0.83	0.66
2007	0.79	0.59	0.44
2008	0.39	0.75	0.60
2009	0.45	0.72	0.58
2010	0.40	0.55	0.44
2011	0.30	0.55	0.41
2012	0.25	0.99	0.80
2013	0.57	0.87	0.64
2014	0.90	0.26	0.21
2015	0.57	0.72	0.57
2016	-0.27	1.29	1.25
2017	0.24	0.96	0.74
2018	0.41	0.82	0.66
2019	0.53	0.85	0.68
2020	0.57	0.93	0.74
2021	0.55	0.81	0.62
2022	0.42	0.82	0.63
2023	0.39	0.90	0.73
2024	0.30	0.95	0.76
Total	0.54	0.83	0.64



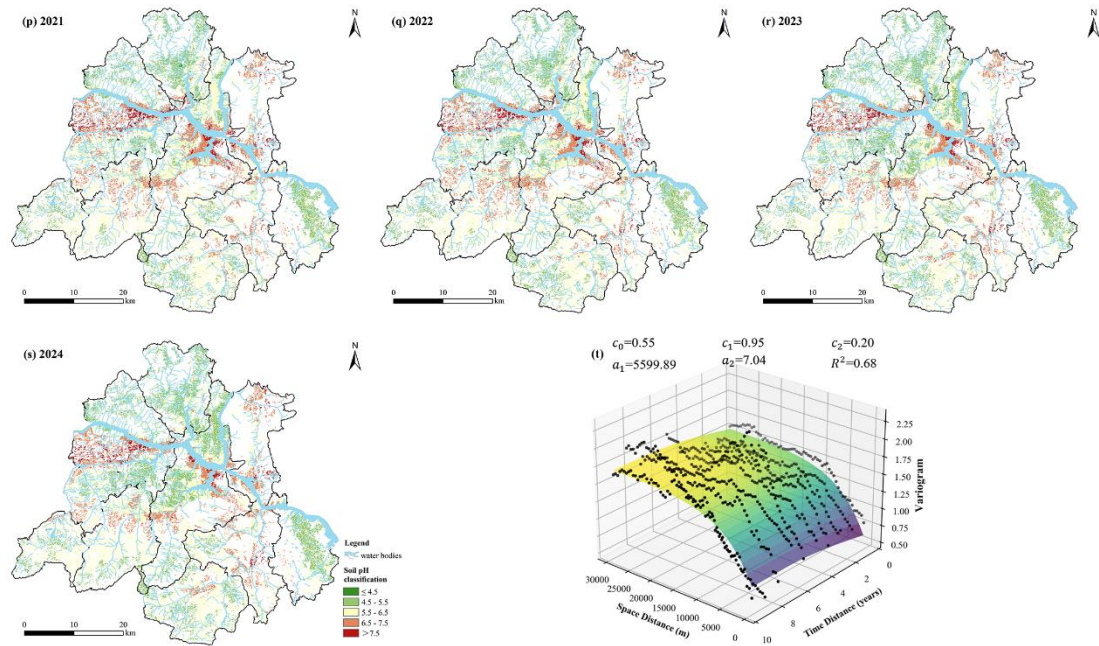


Figure 2. Spatial distribution of soil pH in Zigui County from 2006 to 2024, along with the experimental and theoretical variogram models.

3.3 Spatiotemporal dynamics of soil pH from 2006 to 2024

As shown in Figure 3, the annual mean pH values and area proportions of different pH classes were calculated using the interpolated soil pH data collected for Zigui County from 2006 to 2024. The results reveal that soil pH in Zigui County exhibited an overall fluctuating downward trend from 2006 to 2024, with a cumulative reduction of 0.24 pH units. The temporal variation can be divided into three stages: an initial decline, followed by an increase, and then a subsequent reduction, with turning points occurring in 2010 and 2018. The mean soil pH reached its highest value of 6.19 in 2018 and decreased to its lowest value of 5.92 in 2024. Although the mean pH values in 2017 and 2018 were identical, the proportion of acidic soils in 2018 (66.9%) was slightly lower than that in 2017 (67.7%). Overall, soil pH demonstrated a recovery trend between 2010 and 2018, whereas acidification accelerated markedly from 2018 to 2024. Despite the temporary increase in pH during 2010–2018, acidic soils remained dominant throughout the study area. By 2024, the mean pH had decreased to 5.92, which was even lower than that in the initial year of the study period (2006, 6.16).

In terms of classification results, areas with $\text{pH} < 6.5$ consistently accounted for approximately 70% of the total area, indicating the presence of predominantly acidic soils in Zigui County, while alkaline soils ($\text{pH} > 7.5$) reflected the smallest proportion. Among all pH classes, extremely acidic

soils ($\text{pH} \leq 4.5$) accounted for only a negligible proportion throughout the study period, whereas soils with pH values between 5.5 and 6.5 consistently dominated. Furthermore, the temporal variation in the proportion of acidic soils ($\text{pH} < 6.5$) was generally consistent with the trend in mean pH, demonstrating a pattern of increase, decrease, and subsequent increase. The lowest proportion of acidic soils was recorded in 2018, while the highest was observed in 2024.

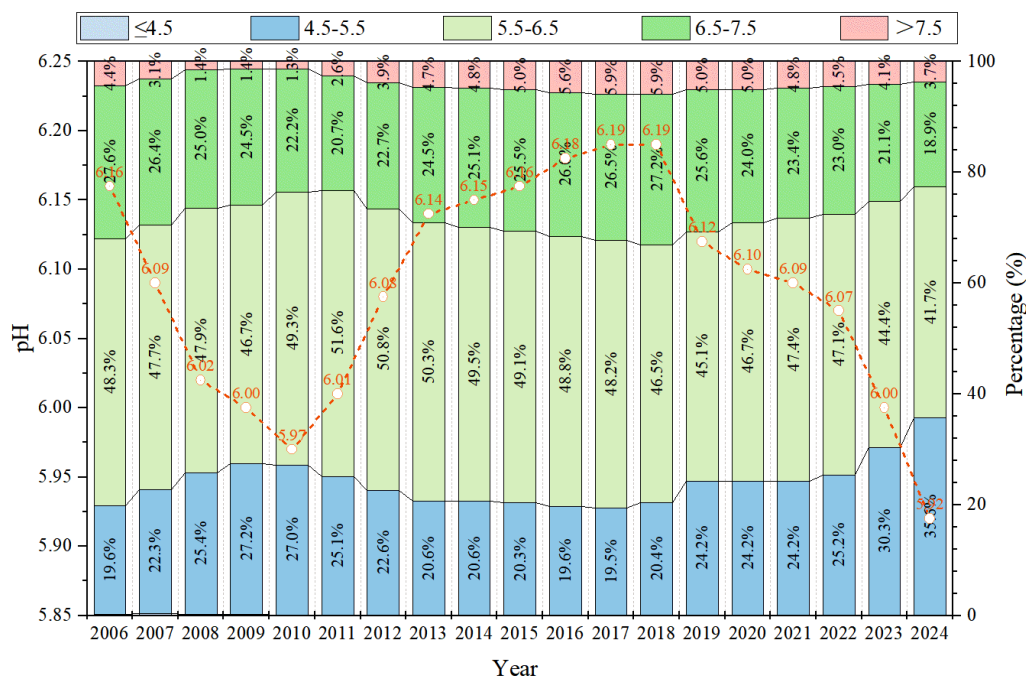


Figure 3. Temporal dynamics of soil pH class distribution and mean soil pH from 2006 to 2024 (The proportion of samples with $\text{pH} \leq 4.5$ was less than 1% and therefore not displayed separately. The left axis indicates mean soil pH, and the right axis shows percentage values.).

3.4 Spatiotemporal characteristics of soil acidification

Aiming to comprehensively analyze the spatiotemporal evolution of soil acidification in Zigui County, soil pH changes ($\Delta\text{pH} = \text{pH}_{2024} - \text{pH}_{2006}$) and the standardized Mann–Kendall statistic (Z) were calculated to quantitatively assess the extent and trends of soil acidification. The results are shown in Table 5 and Figure 4. According to the ΔpH classification results, the total area affected by soil acidification was 231.09 km², accounting for 43.39% of the study area, revealing moderate acidification as the dominant category (21.90%). Conversely, areas with no evident acidification or an increase in pH covered 301.46 km² (56.61%), indicating that soil acidification did not occur uniformly across the study area. Instead, certain regions may have experienced pH recovery due to

natural conditions or anthropogenic management practices. The Mann–Kendall trend test results indicate that areas with a remarkable decreasing trend in soil pH covered 124.89 km² (23.45%), of which extremely substantial reductions accounted for 12.83%. Meanwhile, areas demonstrating a notable increasing trend covered 116.82 km² (21.94%), with extremely substantial increases comprising the dominant category. Overall, the area exhibiting considerable reductions was slightly larger than that exhibiting substantial increases. Combined with the results presented in Section 3.3, soil pH in Zigui County exhibited a fluctuating trend from 2006 to 2024. This finding further emphasizes the strong spatial heterogeneity in soil acidification processes, characterized by the coexistence of regions undergoing acidification and those experiencing pH recovery.

Based on the spatial patterns shown in Figure 5, a high degree of spatial consistency was observed between soil acidification classes and areas exhibiting decreasing soil pH in Zigui County. Areas with substantial reductions in soil pH largely overlapped with severely acidified regions, which were predominantly distributed in orchard areas. These findings indicate that soil acidification not only exhibits an accumulative pattern but also reflects a persistent evolutionary process closely associated with land-use types. Zigui County is dominated by citrus cultivation. Therefore, long-term continuous citrus planting has resulted in sustained uptake of base cations by crops, such as Ca²⁺ and Mg²⁺, despite lacking external replenishment, thereby accelerating base cation depletion (Guo et al., 2023; Wang et al., 2022). Additionally, root exudation and the decomposition of plant residues release organic acids and alter rhizosphere chemistry, further contributing to soil acidification (Bolan et al., 2008). Moreover, the long-term application of ammonium-based fertilizers (e.g., ammonium sulfate and urea) continuously releases H⁺ through nitrification and ion exchange processes, representing one of the major anthropogenic drivers of soil acidification (J.H. Guo et al., 2010). From a natural environmental perspective, the study area features a mountainous and hilly terrain, with cultivated land and orchards mainly distributed along river valleys and sloping areas, resulting in relatively steep slopes and high soil erosion risk. The dominant soil types include yellow, yellow-brown, and purple soils, which are developed from weathered carbonate rocks and clastic rock materials. Although some parent materials possess carbonate buffering capacity, intense precipitation combined with enhanced slope runoff jointly promotes accelerated leaching of base cations, thereby reducing soil buffering capacity and further intensifying the acidification process (Bolan et al., 2003). Overall, soil acidification in Zigui County

can be attributed to the combined effects of anthropogenic management practices and natural geographical conditions. Anthropogenic factors, including fertilization and cropping systems, play a dominant role at local scales, whereas topography–climate interactions enhance spatial heterogeneity at regional scales. These processes jointly form a spatial pattern characterized by the coexistence of localized areas of severe acidification and widespread background-level acidification.

Table 5 Classification of soil pH changes and Mann–Kendall trend test results (2006–2024)

$\Delta\text{pH} = \text{pH}_{2024} - \text{pH}_{2006}$				
Soil acidification classification thresholds		Area （km ² ）	Percentage	Soil acidification classification
$\Delta\text{pH} < -1$		30.11	5.65%	Severe acidification
$-1 \leq \Delta\text{pH} < -0.5$		116.62	21.90%	Moderate acidification
$-0.5 \leq \Delta\text{pH} < -0.3$		84.36	15.84%	Slight acidification
$\Delta\text{pH} \geq -0.3$		301.46	56.61%	No acidification or pH increase
Mann-Kendall trend test				
β	Z	Area (km ²)	Percentage	Trend classification
$\beta < 0$	$Z < -2.58$	68.34	12.83%	Highly significant decrease
	$-2.58 \leq Z < -1.96$	32.92	6.18%	Significant decrease
	$-1.96 \leq Z < -1.65$	23.63	4.44%	Slightly significant decrease
$\beta = 0$	$-1.65 \leq Z \leq 1.65$	290.84	54.61%	No significant change
	$1.65 < Z \leq 1.96$	21.45	4.03%	Slightly significant increase
$\beta > 0$	$1.96 < Z \leq 2.58$	30.98	5.82%	Significant increase
	$Z > 2.58$	64.39	12.09%	Highly significant increase

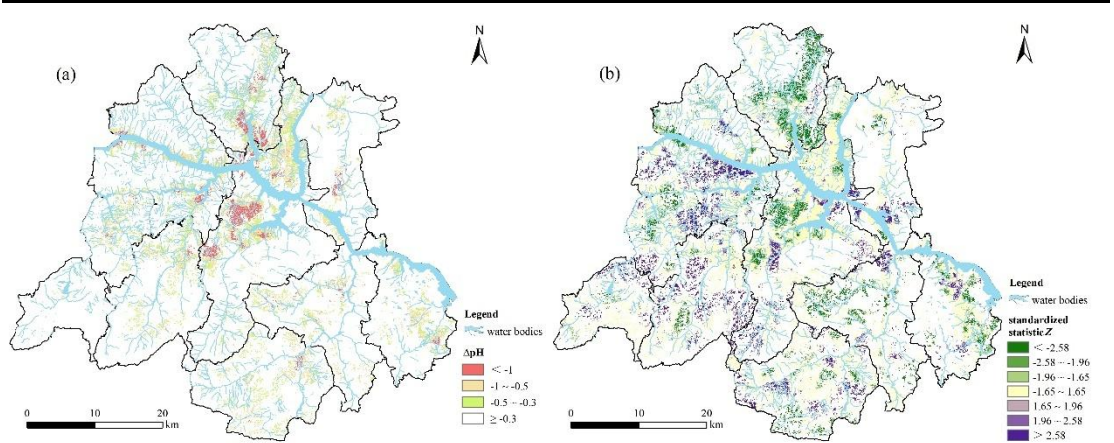


Figure 4. Spatial distribution of soil pH changes (ΔpH) and Mann–Kendall standardized statistic (Z) in Zigui County from 2006 to 2024.

3.5 Variations in stochastic site indicators

3.5.1 Single-point SSI

Aiming to reveal the evolutionary patterns of the single-point indicators under varying ΔpH thresholds (ζ), 100 equally spaced values of ζ were defined within the ΔpH range of the study area. The corresponding indicator functions were calculated using the formulations in Table 1, and the results are presented in Figure 5.

Figure 5(a) shows the variations of RABT with increasing ζ . RABT gradually increases at low values of ζ and rapidly rises when ζ ranges from -1.5 to 0 , with its growth rate gradually decreasing as ζ approaches its upper bound. SIE was used to quantify the sensitivity of RABT to changes in ζ , as indicated by the red dashed line in Figure 5(a). Within the interval $-2.0 \leq \zeta < -1.5$, SIE_RABT exhibits pronounced fluctuations, with greater variability at lower values of ζ (i.e., under more stringent acidification criteria). This trend indicates that RABT is highly sensitive to changes in ζ within the low-threshold region, where small increases in ζ result in substantial changes in the proportion of acidified areas. When $-1.5 \leq \zeta < 0$, SIE_RABT remains negative but gradually increases, accompanied by a continuous reduction in its absolute value. This trend indicates a progressive reduction in the growth rate of RABT, with the curve eventually stabilizing as ζ approaches 0 . These results indicate that, within the range of $-1.5 \leq \zeta < 0$, the rate of increase in the area satisfying the threshold condition gradually decreases, indicating that a considerable proportion of the study area exhibited decreasing pH levels during 2006–2024. At the classification thresholds of $\zeta = -1$, -0.5 , and -0.3 , the corresponding RABT values are 0.06 , 0.28 , and 0.43 , respectively, indicating that 6% , 22% , and 17% of cropland and orchard areas have reached severe, moderate, and slight acidification levels, respectively. These results are consistent with those obtained from the ΔpH -based classification.

Figure 5(b) shows the variations in MBT and MDBT. Both indicators are equal to zero at the minimum value of ζ . When $\zeta < -1$, MBT and MDBT exhibit only minor variations, indicating that severely acidified areas account for only a small proportion of the study area under stringent acidification criteria and that changes in ζ exert limited influence on both indicators. MBT remains

negative across the entire range of ζ , confirming from a weighted-average perspective that croplands and orchards within the study area generally exhibit soil acidification.

CMBT represents the mean ΔpH within the acidified subset, and its variation is shown in Figure 5(c). When $\zeta < -1.5$, SIE_CMBT exhibits pronounced fluctuations, consistent with the pattern observed for SIE_RABT, indicating that the mean ΔpH of acidified locations is highly sensitive to changes in ζ under stringent threshold conditions. When $-1 \leq \zeta < 0$, the absolute value of SIE_CMBT gradually decreases, and CMBT becomes increasingly stable. This trend indicates that newly included acidified locations are primarily distributed within the ΔpH range of -1 to 0 , implying that soil acidification is dominated by moderate and slight acidification.

As shown in Figure 5(d), BTO is defined as the ratio of acidified to non-acidified area. When $\zeta > 0$, BTO increases rapidly, indicating that the proportion of areas exceeding the threshold is relatively small. At the classification threshold of $\zeta = -0.3$, BTO reaches 0.77, indicating that a substantial proportion of cropland and orchard areas have at least reached the level of slight acidification.

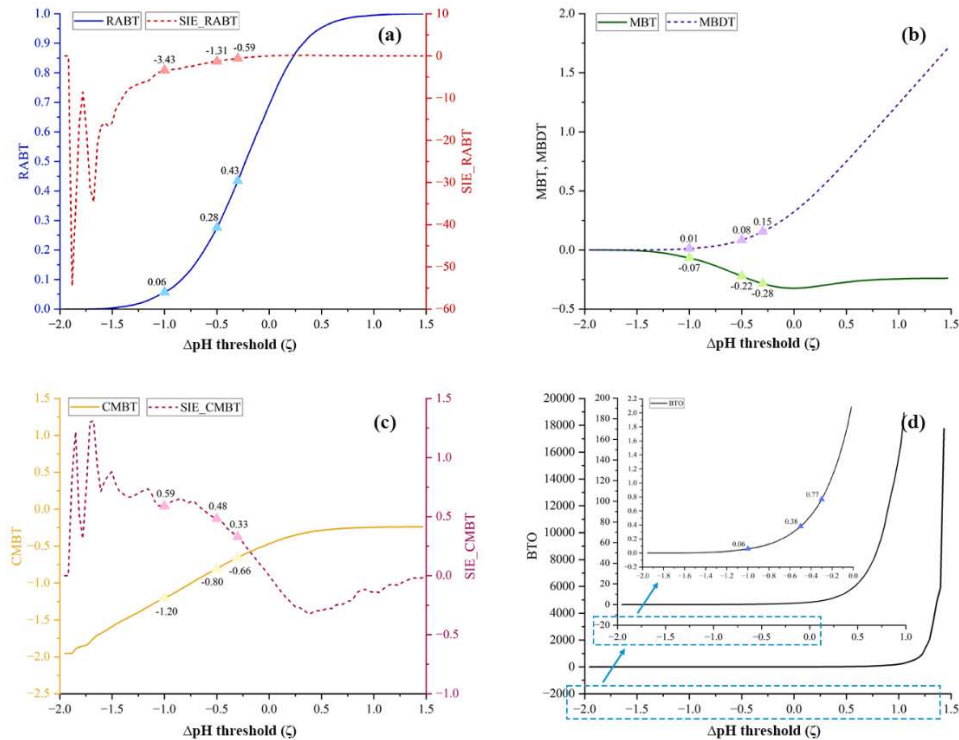


Figure 5. Variations of single-point SSI with ΔpH threshold (ζ) in Zigui County.

3.5.2 Two-point SSI

The threshold was divided into 100 levels, and the corresponding two-point indicator functions were calculated based on the equations presented in Table 2. The results are shown in Figure 6. NIC represents the joint probability that ΔpH values at two spatial locations fall simultaneously below ζ . As shown in Figure 6(a), NIC gradually decreased with increasing spatial distance under the same ζ , whereas it increased with rising ζ at the same spatial distance. This trend indicates that increasing spatial distance reduces the likelihood of two locations simultaneously satisfying the below-threshold condition, indicating the weakening spatial synchrony of areas satisfying the condition $\Delta pH < \zeta$ with increasing distance. These findings reveal that the soil acidification process exhibits strong spatial dependence. Spatially adjacent areas are more likely to experience similar acidification conditions, whereas the consistency of acidification patterns gradually decreases with increasing distance due to variations in topography, land-use patterns, and agricultural management practices. In contrast, increasing ζ allows more locations to satisfy the condition $\Delta pH < \zeta$, thereby increasing the joint probability that two locations simultaneously meet the threshold criterion.

IR further characterizes the spatial aggregation of locations simultaneously satisfying the condition $\Delta pH < \zeta$ and is defined as the ratio between the joint probability that two locations simultaneously satisfy $\Delta pH < \zeta$ and the probability that at least one location satisfies $\Delta pH < \zeta$. As shown in Figure 6(f), IR increased with rising ζ under the same spatial distance but decreased with increasing spatial distance under the same ζ . This trend indicates that, at higher ζ values, areas satisfying the condition $\Delta pH < \zeta$ are more likely to form spatial connections, while increasing spatial distance weakens the spatial association among these areas. However, when the spatial distance was less than 1000 m, IR remained high across different ζ values, indicating strong local-scale spatial aggregation among areas satisfying $\Delta pH < \zeta$ and reflecting prevalent small-scale clustering in the soil acidification process. These results further indicate that soil acidification in the cropland and orchard areas of Zigui County was mainly observed in localized clusters. Neighboring areas are likely affected by similar natural environmental conditions and agricultural management practices, increasing their tendency to exhibit comparable degrees of soil acidification.

CIC represents the spatial correlation after eliminating the influence of the overall occurrence probability (RABT) of below-threshold areas and illustrates the spatial aggregation of these areas relative to a random distribution. As shown in Figure 6(b), high CIC values indicate strong spatial aggregation of areas satisfying the condition $\Delta pH < \zeta$ at the corresponding spatial scale. When ζ

approached the minimum value of the dataset, only a few locations satisfied the condition; conversely, when ζ approached the maximum value, most locations satisfied the criterion. Under the two extreme conditions, the weakened spatial variation of the indicator variable resulted in CIC values that approach zero. Around the slight acidification threshold ($\zeta \approx -0.3$), CIC reached its maximum across different spatial distances, indicating that areas satisfying the condition $\Delta\text{pH} < \zeta$ exhibited the strongest spatial aggregation. CIC gradually decreased with increasing spatial distance, demonstrating that the spatial aggregation of soil acidification in cropland and orchard areas of Zigui County mainly occurred at local scales, while spatial associations weakened at larger spatial scales. Overall, these results indicate that the slight acidification threshold ($\zeta \approx -0.3$) effectively captures the spatial organization of soil acidification in the study area. Although the RABT analysis showed that moderately acidified areas accounted for the largest proportion of the study area, the spatial aggregation was mostly concentrated at the slight acidification threshold. This finding indicates that once soil acidification reaches the slight acidification stage, its spatial organization has already become relatively stable and continuous. Therefore, $\zeta \approx -0.3$ can be regarded as a critical threshold for identifying the spatial differentiation of soil acidification and providing early warnings of soil acidification risk.

NBC describes the joint spatial variation characteristics of ΔpH values when both locations satisfy the condition $\Delta\text{pH} < \zeta$. As shown in Figure 6(c), when the spatial distance was less than 1000 m, NBC continuously increased with rising ζ . This finding indicates that, at the local scale, expanding the threshold included additional locations that satisfy the condition $\Delta\text{pH} < \zeta$ as well as locations with similar ΔpH variations, thereby enhancing the spatial consistency of ΔpH variations within areas meeting the condition $\Delta\text{pH} < \zeta$. When the spatial distance exceeded 1000 m, NBC exhibited an increasing–decreasing trend with rising ζ . This trend indicates that, at larger spatial scales, increasing ζ initially enhanced the joint spatial variation between locations, whereas further increments incorporated additional areas with heterogeneous ΔpH characteristics, resulting in reduced spatial consistency. Under the same threshold condition, NBC decreased with increasing spatial distance, indicating a clear distance-decay pattern in the joint spatial variation of ΔpH . These findings further complement the NIC results, demonstrating that locations simultaneously satisfying the condition $\Delta\text{pH} < \zeta$ not only have a higher probability of joint occurrence but also exhibit more similar ΔpH variation characteristics. This trend indicates that neighboring areas are not only more

likely to undergo soil acidification simultaneously but are also more likely to exhibit similar acidification patterns.

DBC characterizes the spatial correlation of the deviation of ΔpH values from ζ under below-threshold conditions. As shown in Figure 6(d), the overall variation pattern of DBC was similar to that of NIC. Under the same spatial distance, DBC increased with rising ζ , indicating that higher ζ included additional locations satisfying the condition $\Delta\text{pH} < \zeta$ with similar deviations from the threshold, further improving the spatial consistency within below-threshold areas. This finding implies that ΔpH variations exhibited stronger spatial dependence under larger ζ . Under the same ζ value, DBC decreased with increasing spatial distance, indicating the weakening similarity of threshold-deviation patterns between locations with increasing spatial distance. However, the decline in DBC was relatively gradual, implying that ΔpH variations within below-threshold areas maintained strong spatial continuity and that acidification-related processes exhibited certain spatial persistence. Combined with the NBC results, these findings reveal that neighboring locations not only exhibit similar ΔpH variation characteristics but also demonstrate a high degree of consistency in their deviation from the threshold. Furthermore, neighboring areas not only exhibit similar soil pH variation trends but also similar degrees of deviation from the same acidification threshold, reflecting the stable local-scale spatial continuity of the soil acidification process.

CBC describes the conditional spatial dependence between ΔpH values under the constraint of $\Delta\text{pH} < \zeta$. As shown in Figure 6(e), CBC decreased with rising ζ under the same spatial distance, indicating that high ζ values incorporated additional areas with different ΔpH characteristics into the conditional analysis and reduced the consistency of ΔpH variations within below-threshold areas. Under the same ζ , CBC showed only minor changes with increasing spatial distance, indicating the relative insensitivity of the conditional spatial dependence to spatial separation. Therefore, ΔpH variations within below-threshold areas maintained relatively stable spatial associations even across large spatial scales. These results indicate that, after accounting for the occurrence condition of soil acidification, areas satisfying the condition $\Delta\text{pH} < \zeta$ still exhibit stable conditional spatial dependence, revealing that ΔpH variations within acidified areas are not randomly distributed but instead possess a certain spatial organization structure. This finding implies that, within areas satisfying the acidification condition, different locations still maintain relatively consistent variation patterns, reflecting strong local-scale spatial homogeneity in the soil acidification process.

Overall, the two-point indicator analysis quantitatively characterized the spatial associations among areas satisfying the condition $\Delta\text{pH} < \zeta$ across different spatial scales and threshold conditions. The results further revealed the spatial organization patterns underlying the spatial clustering characteristics determined through the ΔpH classification results and MK trend analysis in Section 3.4. Through the integration of multiple aspects, including joint occurrence probability, spatial aggregation, ΔpH variation consistency, and threshold deviation, this analysis provided a comprehensive description of spatial structure of soil pH variations in cropland and orchard areas of Zigui County, demonstrating prevalent spatial aggregation and spatial dependence. Combined with the single-point indicator analysis, these results further confirm that soil acidification processes in cropland and orchard areas of Zigui County were evident during 2006–2024, and that areas satisfying the condition $\Delta\text{pH} < \zeta$ exhibited substantial spatial clustering characteristics. Therefore, effective regional soil acidification management should incorporate long-term fixed-point monitoring systems and implement targeted soil improvement and field management strategies based on the small-scale spatial differentiation characteristics of acidification patterns.

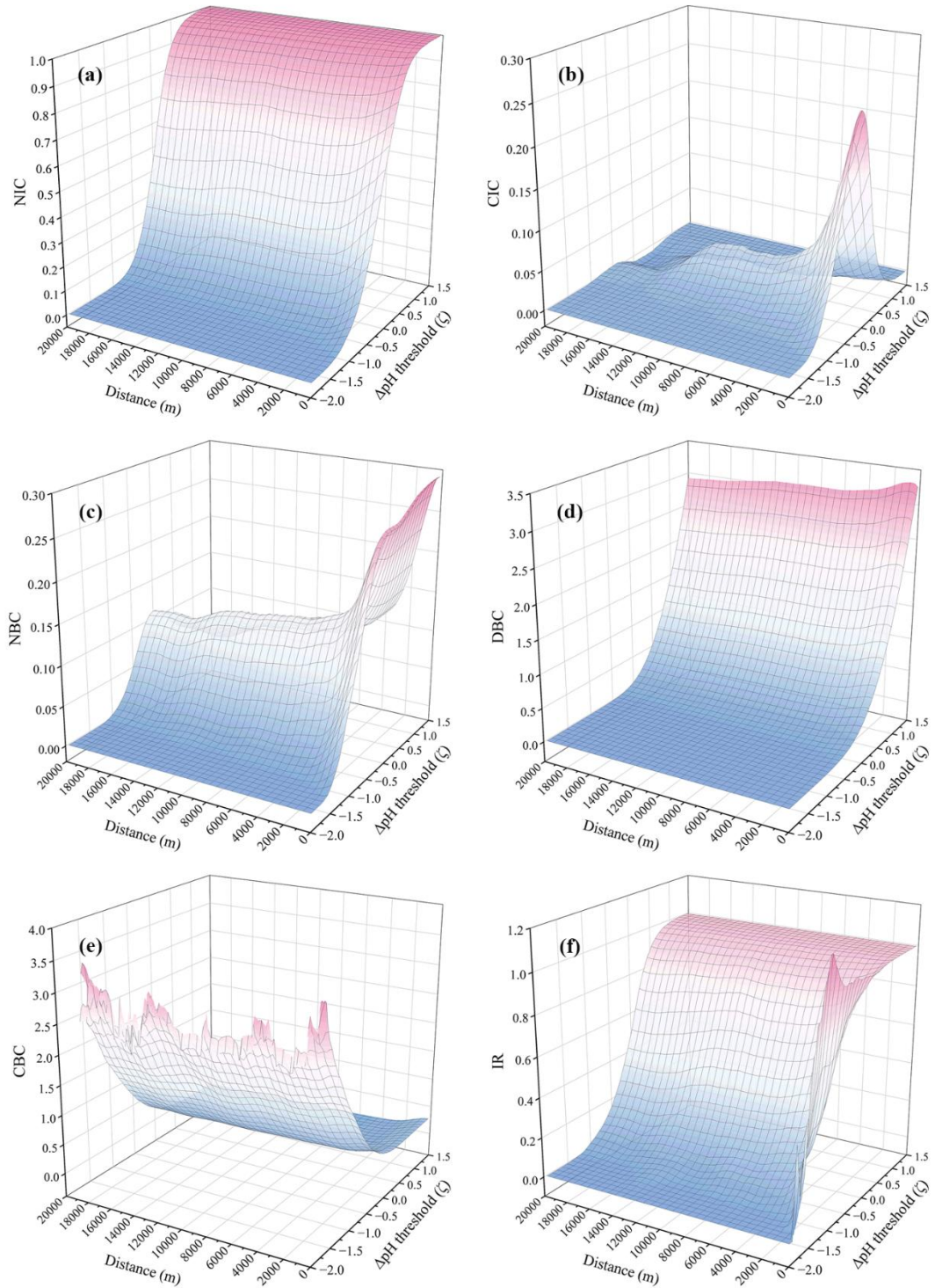


Figure 6. Variations of two-point indicator functions with ΔpH threshold (ζ) in Zigui County.

4 Conclusions

In this study, a continuous soil pH dataset was developed for Zigui County during 2006–2024 using spatiotemporal kriging, and an SSI-based framework was established to quantify the spatial uncertainty of soil acidification. Different from traditional approaches that mainly focus on the

spatial distribution and temporal trends of soil acidification, this study used single- and two-point indicators to systematically assess the spatial uncertainty of soil acidification in terms of acidification occurrence probability, variation characteristics, and spatial associations under different threshold conditions. The results showed that soil acidification processes in cropland and orchard areas of Zigui County were evident during 2006–2024, and different acidification classes exhibited stronger spatial aggregation rather than random distribution, with pronounced spatial associations observed at local scales. Among them, single-point indicators revealed the spatial differences in acidification occurrence under different ζ conditions, while two-point indicators further quantified the spatial dependence, aggregation characteristics, and scale effects of areas satisfying $\Delta\text{pH} < \zeta$. The proposed SSI framework in this study presents a new approach for quantitatively analyzing the spatial uncertainty of soil acidification and contributes to a deeper understanding of the spatial differentiation processes of regional soil acidification. Overall, the results highlight the importance of incorporating threshold-based spatial uncertainty into regional soil acidification assessments and establish a scientific basis for long-term monitoring, risk identification, and precision soil management.

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