

Article

Spatial Differentiation of Soil Organic Carbon and Its Geochemical Driving Mechanisms in the Hulan River Basin, Northeast China

Kai Liu ^{1,2}, Keke Xu ^{1,2,*}, Yunhong Song ^{1,2}, Chaoqun Chen ^{1,2}, Huimin Dai ^{1,2} and Minghui Wei ^{1,2,*}

¹ Key Laboratory of Black Soil Evolution and Ecological Effect, Ministry of Natural Resources/Liaoning Province, Shenyang 110034, China; liu.kai@mail.cgs.gov.cn (K.L.); songyunhong@mail.cgs.gov.cn (Y.S.); m15754300125@163.com (C.C.); daihuimin78@126.com (H.D.)

² Shenyang Center of China Geological Survey, Northeast Geological S&T Innovation Center of China Geological Survey, Shenyang 110034, China

* Correspondence: xukeke@mail.cgs.gov.cn (K.X.); weiminghui@mail.cgs.gov.cn (M.W.)

Abstract

Soil organic carbon (SOC) is central to terrestrial carbon cycling, soil health and sustainable land utilization. However, in Northeast China's black soil region, the quantitative synergistic regulatory mechanisms of soil geochemical background, climate, and topography on SOC spatial heterogeneity remain poorly understood, limiting targeted sustainable soil carbon management. This study took the Hulan River Basin with a complete soil geochemical gradient as the study area. Based on eight major soil elements and pH data, we divided the basin into five geochemical zones via PCA and K-means clustering (cumulative variance contribution: 83.02%). SOC content differed significantly among zones, peaking in strongly acidic residual-slope zones and bottoming in alkaline saline-alkali alluvial zones. Geodetector results showed aridity ($q = 0.57$), mean annual temperature ($q = 0.50$), and geochemical zone ($q = 0.46$) dominated SOC differentiation. The non-linear interaction between geochemical zone and aridity exhibited the strongest explanatory power ($q = 0.63$), far exceeding individual effects, as revealed by the interaction detector. A dual regulatory mechanism was identified: iron–manganese oxides stabilize SOC via organo–mineral complexation, while high pH and base cations accelerate SOC decomposition by disrupting soil aggregates. This study clarifies the synergistic controls of pedogeochemistry, climate and topography on black soil SOC patterns, highlighting the underestimated dominant role of geochemical background. The findings support precise regional carbon stock assessment and differentiated carbon sequestration strategies.

Keywords: geochemical zoning; soil organic carbon; driving mechanism; geodetector; Hulan River Basin; black soil; sustainable land management

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1. Introduction

Soil organic carbon (SOC) constitutes the largest carbon pool in terrestrial ecosystems, and its storage, stability, and spatial differentiation profoundly regulate global carbon cycling, climate change, and soil health [1,2]. As a key grain-producing area and a typical soil zone rich in organic carbon in China, the black soil region of Northeast China has experienced rapid SOC loss and intensified spatial heterogeneity due to long-term cultivation and environmental changes [3–5]. Accurate identification of its driving

mechanisms holds irreplaceable scientific value and strategic significance for enhancing regional carbon sinks, protecting black soils, and ensuring food security [6].

Current research on SOC spatial variability at the regional scale has mostly focused on external drivers such as climate, topography, vegetation, and human activities [7–9]. In the black soil region of Northeast China, numerous studies have identified temperature, precipitation, aridity, and elevation as dominant external factors controlling SOC spatial differentiation [10], with a general spatial pattern of “high in the northeast and low in the southwest” [11]. However, such studies have generally underestimated the intrinsic control of soil geochemical background [12,13]. The geochemical background, composed of parent material, elemental composition, acid–base conditions, and mineral properties, not only determines soil physical structure and microenvironment [14] but also directly governs SOC sequestration potential and decomposition rate through organo–mineral complexation, aggregate stabilization, and microbial metabolic regulation [15], representing a fundamental driver of SOC spatial differentiation.

Globally, mechanistic studies have confirmed that iron, aluminum and manganese oxides can form stable organo–mineral complexes via adsorption and co-precipitation, significantly enhancing SOC persistence [16–18]. Base cations such as calcium and magnesium, together with pH, bidirectionally regulate carbon sequestration and mineralization by altering colloid stability, organic matter solubility, and microbial community structure [19]. In saline–alkali and high-sodium environments, the disruptive effect of base cations on aggregates is particularly pronounced, directly accelerating SOC mineralization and loss [20]. However, at the full watershed scale in the black soil region of Northeast China, systematic quantitative analyses are lacking on how soil geochemical properties couple with climate and topography to drive SOC spatial patterns [21], as well as on their relative contributions and non-linear interaction mechanisms [21]. This limits accurate assessment of the carbon pool and the formulation of differentiated carbon sequestration strategies in black soil regions [22].

To visualize and quantify the coupling between SOC and diverse geochemical indicators, geostatistical spatialization and multivariate statistics are standard tools in soil carbon research [23]. Geostatistical interpolation transforms discrete sampling data into continuous spatial layers to reveal the spatial heterogeneity of SOC and major soil elements. Principal component analysis (PCA) serves as a powerful dimensionality reduction technique that processes multi-elements to identify key geochemical assemblages that govern soil formation and carbon dynamics [24]. The integration of PCA with K-means clustering subsequently delineates geochemical zones with unique mineral and elemental features, creating a framework for understanding spatial patterns in complex geological settings. This combined approach has been effectively demonstrated in studies of Archean granitoids [25], lithium exploration in Sweden [26], and soil quality assessment in Egypt’s El-Fayoum Depression [24], where PCA reduced numerous soil parameters into interpretable principal components that captured the essential variability in soil properties. The Geodetector model represents a significant advancement in quantifying driving mechanisms, using the q-statistic to measure both the independent effects and interaction patterns of geochemical and environmental factors on SOC spatial variation [27]. The q-statistic provides a rigorous quantitative framework for understanding how natural and anthropogenic factors interact to influence SOC distribution, moving beyond simple correlation analyses to reveal complex causal relationships. However, most existing studies tend to adopt these methods separately rather than constructing a coordinated integrated analytical framework. The integration of these three methodological pillars—geostatistical interpolation for spatial continuity, PCA-K-means for geochemical zoning, and Geodetector for quantitative driver analysis—represents a frontier in soil carbon research that could significantly advance our understanding of SOC dynamics across complex environmental

gradients [28]. Such an integrated framework would enable researchers to not only map SOC distribution accurately but also to understand how different geochemical provinces exhibit varying sensitivities to environmental and anthropogenic drivers, ultimately supporting more precise and effective soil carbon management policies at watershed and regional scales.

Located in the core black soil area of the eastern Songnen Plain, the Hulan River Basin exhibits a continuous geochemical gradient from east to west: acidic residual-slope deposits, loess-like parent materials, and alkaline saline-alkali alluvial deposits. This gradient is highly coupled with hydrothermal conditions and topography, providing an ideal natural laboratory for revealing SOC spatial differentiation driven by multi-factor synergy [29]. Accordingly, this study took surface soils of the Hulan River Basin as the research object; systematically measured eight major elements and pH; constructed a geochemical zoning framework using principal component analysis (PCA) and K-means clustering; and quantified the independent contributions and interactive effects of climate, topography, geochemistry, and other factors on SOC spatial heterogeneity using the geodetector [30]. We aimed to clarify the key mechanisms by which the geochemical background regulates SOC accumulation and loss. The study addressed three questions: (1) How do soil geochemical characteristics vary spatially across the basin, and can geochemical zones with distinct carbon functions be identified? (2) What are the relative contributions of climate, topography, and geochemical factors to SOC spatial differentiation, and do significant non-linear interactions exist? (3) What are the core geochemical driving mechanisms of SOC spatial patterns in black soil regions?

2. Materials and Methods

2.1. Study Area Overview

The Hulan River Basin is situated in the eastern Songnen Plain, Northeast China (126°30′–127°30′ E, 46°00′–47°00′ N), serving as a first-order tributary of the Songhua River. The basin covers approximately 34,000 km² and lies within the core zone of the typical black soil region of Northeast China (Figure 1). The study area has a mid-temperate continental monsoon climate with distinct seasons: long, cold winters and warm, humid summers. Mean annual temperature ranges from 0.9 to 4.1 °C, and mean annual precipitation ranges from 441 to 733 mm, concentrated in summer. Evaporation is intense, and aridity increases significantly from east to west, creating a clear spatial gradient of hydrothermal conditions.

The terrain slopes stepwise from east to west, transitioning successively from hilly terraces of the Lesser Khingan Mountains foothills, diluvial-alluvial high plains, to low plains along the Songhua River. Controlled by topography and sedimentary environment, pedogenic parent materials show strong spatial differentiation: the eastern hilly area is dominated by acidic residual and slope deposits; the central area features thick loess-like silty clay; the western low plain consists mainly of alluvial and lacustrine deposits, with flat terrain, poor drainage, and widespread salinization. Correspondingly, soil types exhibit clear spatial transitions: the east is dominated by typical black soils and chernozems, the center by chernozems and meadow soils, and the west is extensively dominated by meadow soils, bog soils, saline-alkali soils, and aeolian sandy soils.

Land use in the basin is dominated by cultivated land with a high reclamation rate, and natural vegetation comprises temperate coniferous–broad-leaved mixed forests and meadow steppes. Influenced by hydrothermal conditions, parent material types, and topographic differentiation, the basin forms a continuous geochemical gradient from east to west: an acidic, Si–Al-rich environment; a neutral loess environment; and an alkaline, base-rich environment, providing favorable conditions for studying soil organic carbon (SOC) spatial differentiation and its driving mechanisms.

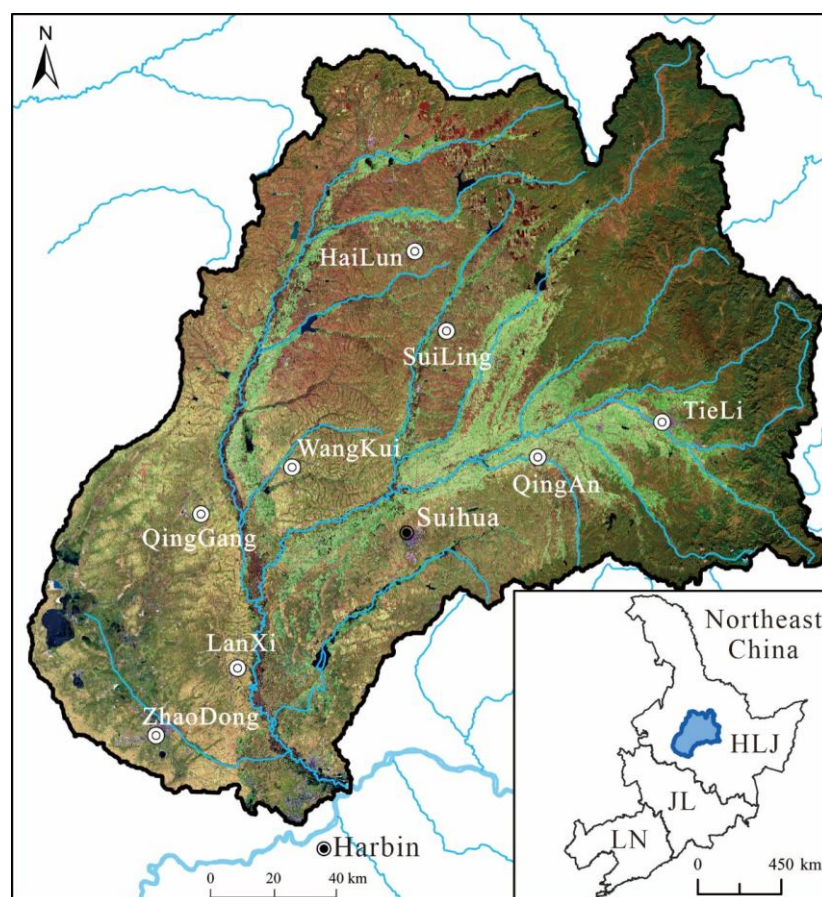


Figure 1. Location of Hulan River Basin. HLJ—Heilongjiang Province; JL—Jilin Province; LN—Liaoning Province.

2.2. Soil Sampling and Analysis

Soil sampling was conducted across the Hulan River Basin from 2021 to 2023 using a systematic grid design at a density of 1 sample per km², with a sampling depth of 20 cm. Each sample was a composite of 3–5 subsamples within a 50 m radius. Sampling sites were selected to represent different land uses (cropland, forest, grassland, etc.), topographic positions, and soil types.

All soil samples were air-dried, cleared of debris and roots, and sieved through a 2 mm nylon sieve before analysis. SOC was determined using the potassium dichromate oxidation–external heating method. Compared with dry combustion (elemental analyzer), the standard reference method, dichromate oxidation may slightly underestimate SOC by 3–5% in soils with organic carbon content [31]. However, this method is stable and reliable in acidic black soils with high organic matter, and the deviation is negligible for regional spatial analysis. Soil pH was measured with a pH meter in a suspension with a soil–water ratio of 1:2.5. Concentrations of major soil elements including silicon dioxide (SiO₂), aluminum oxide (Al₂O₃), iron(III) oxide (Fe₂O₃), manganese (Mn), potassium oxide (K₂O), sodium oxide (Na₂O), calcium oxide (CaO), magnesium oxide (MgO) were determined by X-ray fluorescence (XRF) spectrometry (Thermo Fisher Scientific, Ecublens, VD, Switzerland).

Analytical procedures followed the rigorous quality control protocols of the Regional Multi-Purpose Geochemical Survey Project organized by the China Geological Survey [32]. The QA/QC framework included both internal and external measures to ensure analytical precision [33]. For internal quality control, soil reference materials (GBW series) were interspersed after every 500 samples to monitor accuracy, with the requirement that the qualification rate for each element exceed 90%. For SOC, duplicate analyses were

conducted on 10% of samples, with relative standard deviations (RSD) consistently below 5%, meeting CGS technical specifications. External quality assessment incorporated blind reference materials (BRMs), with four BRMs included per 50-sample batch. Acceptance criteria were defined based on logarithmic disparity and standard deviation between observed and provisional BRM values. An element was deemed acceptable if its qualification rate exceeded 90% and the correlation coefficient between measured and certified BRM values was ≥ 0.9 .

2.3. Collection and Processing of Environmental Factor Data

All environmental factor data were unified into a common coordinate system and resampled to 1 km resolution.

Climate data: mean annual temperature (TMP), annual precipitation (PRE), and the aridity index (Dry) were calculated from 20-year datasets [34].

Topographic data: digital elevation model (DEM) data were derived from ASTER GDEM, from which elevation (EL) was extracted.

Biological data: annual net primary productivity (NPP) data were obtained from MODIS satellite products.

Land use data: land use type (LU) data were interpreted from Landsat images [35]; soil type (ST) data were digitized from the Second National Soil Survey map [36].

2.4. Data Analysis

Descriptive statistics: mean, standard deviation, and coefficient of variation were calculated for each geochemical index. Pearson correlation analysis was used to examine relationships with SOC.

Inverse distance weighting (IDW): Spatial interpolation based on the inverse distance weighting algorithm was performed using ArcGIS Pro 3.7 software.

Principal component analysis (PCA) and geochemical zoning: PCA was performed on eight major elements and pH to reduce dimensionality and identify core compositional factors controlling element distribution. K-means clustering was then applied to the scores of the first three principal components, with the optimal number of clusters determined by the silhouette coefficient, yielding distinct geochemical zones (GZ) across the study area. This workflow converts complex geochemical data into discrete, spatially explicit zones to facilitate mechanistic interpretation and management applications, and the entire PCA-K-means zoning procedure was realized via R scripts.

Geodetector: the geodetector's factor, risk, and interaction detector modules were run in R to quantitatively assess the explanatory power (q-statistic) of environmental factors in SOC spatial differentiation, identify intervals with significant differences in SOC content, and detect interaction types between factors [30].

Since the geodetector requires categorical input variables, all continuous environmental factors (TMP, PRE, Dry, EL, NPP) were spatially discretized. To determine the optimal discretization scheme, three methods (natural breaks, quantiles, and equal intervals) were compared (Figure S1), and the scheme yielding the highest q-statistic in the factor detector was selected. Finally, TMP and PRE were divided into nine categories using natural breaks; Dry into eight categories using quantiles; and EL and NPP into nine categories using natural breaks (Figure S2).

Sensitivity Analysis: Sensitivity analysis was conducted to verify the robustness of PCA-K-means clustering and geodetector discretization schemes. For clustering, cluster numbers from 3 to 6 were tested, and K = 5 showed the highest silhouette coefficient (0.72), indicating the optimal and stable geochemical zoning result. For geodetector discretization, natural breaks, quantiles, equal intervals, geometric intervals, and standard deviation methods were compared. The adopted discretization scheme achieved the highest q-

statistic, while alternative schemes reduced explanatory power by 6–12%. These results confirm that the selected methods are reliable and not sensitive to parameter changes.

3. Results

3.1. Basic Characteristics and Spatial Differentiation of Soil Geochemical Indicators

The SOC content across the study basin ranged widely from 0.20% to 10.29%, with a median value of 2.13% and an average concentration of 2.50% (Table 1). These SOC levels are consistent with regional data from national soil surveys conducted in Northeast China [37] and are notably higher than the national average.

Surface soils in the Hulan River Basin show typical aluminosilicate characteristics, with average concentrations in the order: silicon dioxide (SiO_2 , 62.37%) > aluminum oxide (Al_2O_3 , 13.84%) > iron(III) oxide (Fe_2O_3 , 4.73%) > calcium oxide (CaO , 2.56%) > potassium oxide (K_2O , 2.44%) > sodium oxide (Na_2O , 1.57%) > magnesium oxide (MgO , 1.50%) > manganese (Mn , 0.08%). SiO_2 , Al_2O_3 , and Fe_2O_3 together account for approximately 80% of the total. Coefficients of variation (CV) differ markedly among elements (Table 1): SiO_2 , Al_2O_3 , and K_2O show weak variability (CV < 10%), indicating uniform distribution and high stability across the basin, with little influence from pedogenic processes or external disturbances. In contrast, CaO has an extremely high CV of 0.85, indicating strong spatial heterogeneity (Figure 2g). MgO (CV of 20%), Mn (CV of 24%), Na_2O (CV of 18%), and pH (CV of 19%) show moderate variability, reflecting distinct regional differentiation within the basin.

Mean soil pH was 7.02, ranging from 4.44 to 10.82, with a typical bimodal frequency distribution (Figure 2i), clearly indicating the coexistence of acidic and alkaline zones and a continuous pH gradient from acidic to alkaline across the study area. This pattern closely matches the east-to-west transition of parent material types in the basin.

Spatially, major elements show regular regional differentiation (Figure 3). High values of SiO_2 , Al_2O_3 , Fe_2O_3 , Mn , and K_2O occur in the eastern basin, with low values in the southwest; Na , Ca , and Mg show the opposite pattern, with high values in the southwest and low values in the east. This spatial pattern is highly consistent with the distribution of acidic residual-slope parent materials in the east and alkaline saline–alkali alluvial parent materials in the west, laying a foundation for subsequent geochemical zoning and analysis of SOC driving mechanisms.

Table 1. Descriptive statistics of SOC and major element content in the Hulan River Basin.

Element	Mean	SD	Min	Median	Max	CV/%	Analytical RSD/%
SOC	2.50	1.16	0.20	2.13	10.29	46	0.03
SiO_2	62.37	3.72	41.87	63.50	85.00	6	0.08
Al_2O_3	13.84	0.71	4.79	13.98	16.20	5	0.20
CaO	2.56	2.16	0.86	1.54	15.03	85	2.11
Fe_2O_3	4.73	0.47	1.12	4.77	10.49	10	0.16
K_2O	2.44	0.15	1.17	2.45	3.48	6	0.90
MgO	1.50	0.30	0.51	1.42	4.33	20	2.89
Mn	0.08	0.02	0.02	0.07	0.35	24	0.34
Na_2O	1.57	0.28	0.75	1.51	4.41	18	1.10
pH	7.02	1.30	4.44	6.74	10.82	19	0.50

Note: SOC: soil organic carbon; SiO_2 : silicon dioxide; Al_2O_3 : aluminum oxide; Fe_2O_3 : iron (III) oxide; Mn : manganese; K_2O : potassium oxide; Na_2O : sodium oxide; CaO : calcium oxide; MgO : magnesium oxide. SD: standard deviation. SOC and Oxides are in wt%; pH is dimensionless.

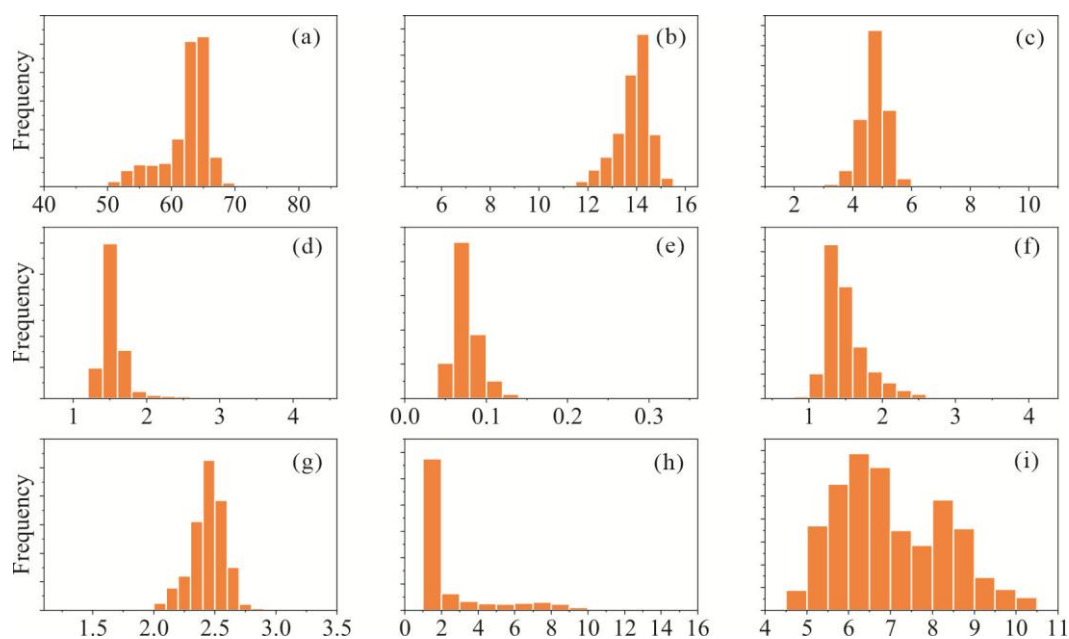
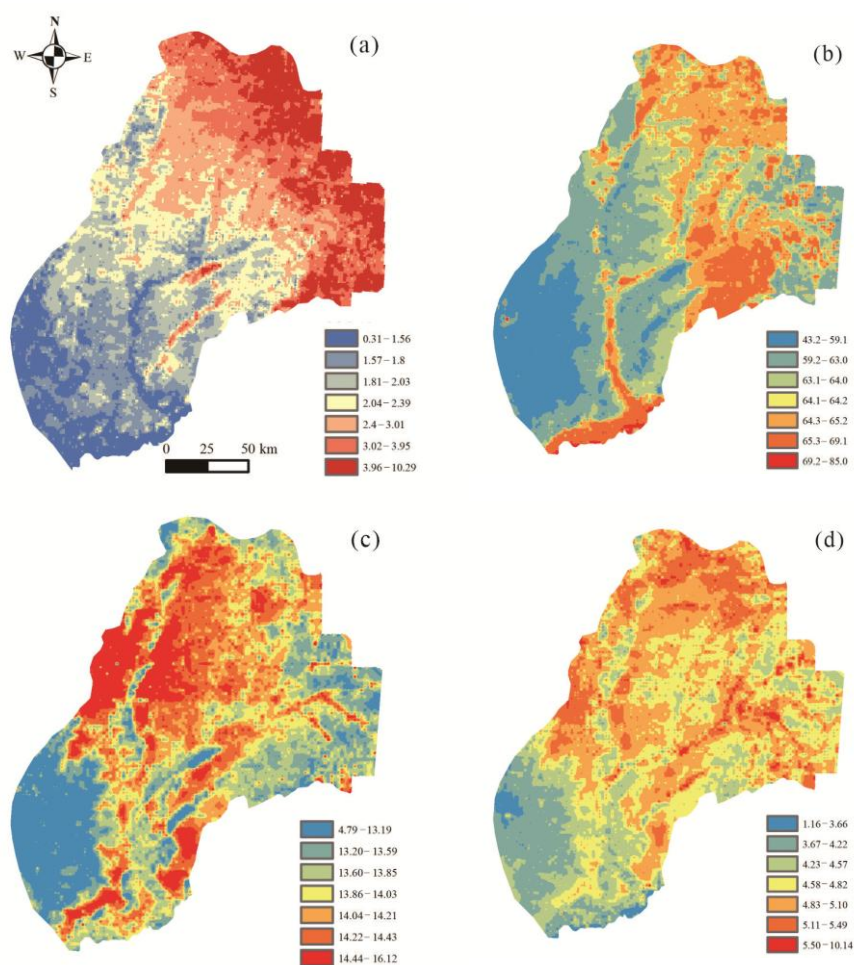


Figure 2. Statistical histogram of geochemical indicators: (a) silicon dioxide (SiO_2); (b) aluminum oxide (Al_2O_3); (c) iron (III) oxide (Fe_2O_3); (d) manganese (Mn); (e) potassium oxide (K_2O); (f) sodium oxide (Na_2O); (g) calcium oxide (CaO); (h) magnesium oxide (MgO); (i) pH. PH is dimensionless; other units are %.



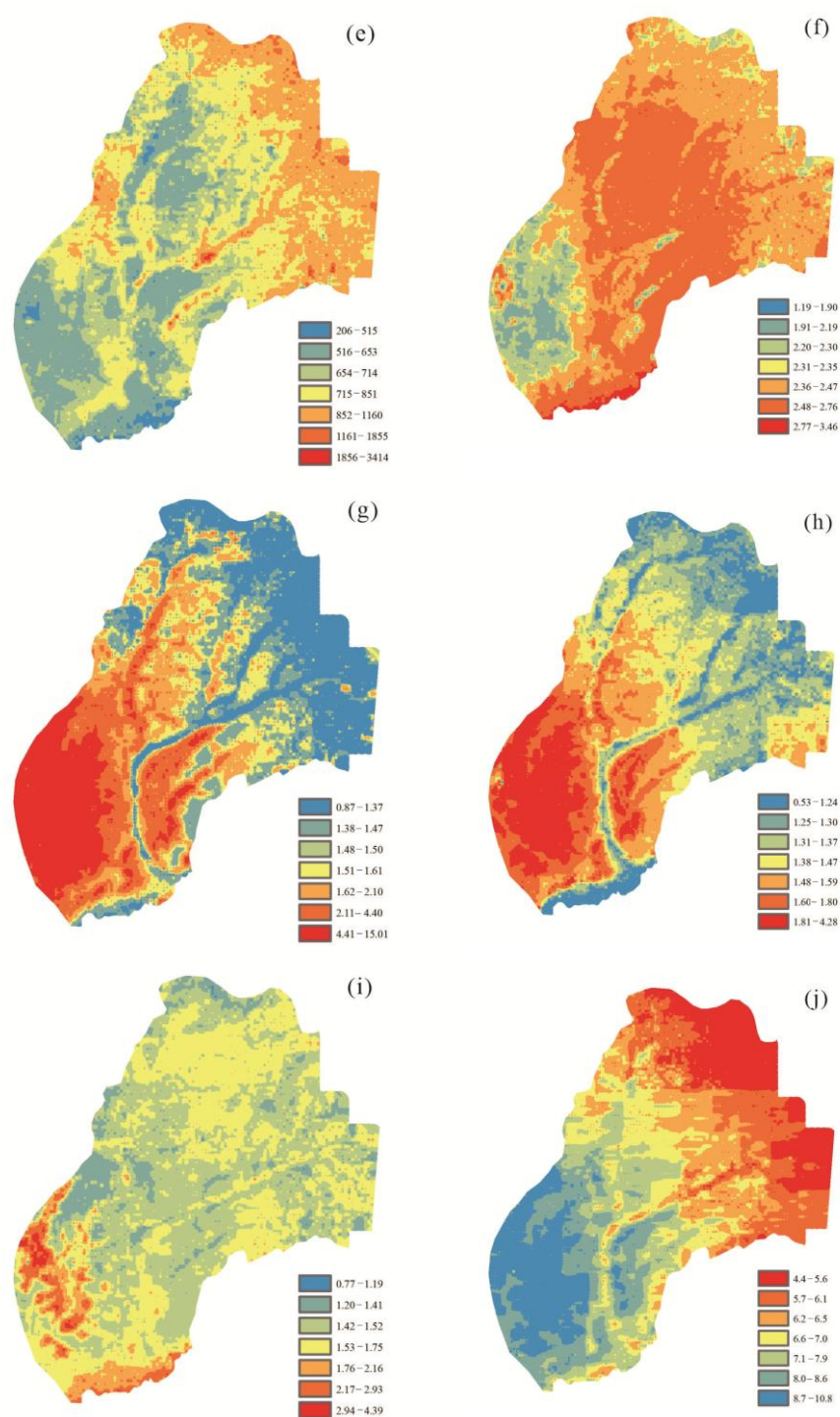


Figure 3. Soil geochemical maps of the Hulan River Basin: (a) soil organic carbon (SOC); (b) silicon dioxide (SiO_2); (c) aluminum oxide (Al_2O_3); (d) iron (III) oxide (Fe_2O_3); (e) manganese (Mn); (f) potassium oxide (K_2O); (g) sodium oxide (Na_2O); (h) calcium oxide (CaO); (i) magnesium oxide (MgO); (j) pH. PH is dimensionless; other units are %.

3.2. Correlations Between Geochemical Indicators and SOC, and Principal Component Analysis

Fe_2O_3 and Mn show extremely significant positive correlations with SOC ($p < 0.01$), with correlation coefficients of 0.41 and 0.51, respectively (Figure 4), indicating that these two elements strongly promote SOC accumulation and stabilization. In contrast, pH, MgO , CaO , and Na_2O show extremely significant negative correlations with SOC ($p < 0.01$), with

coefficients of -0.63 , -0.41 , -0.35 , and -0.31 , respectively, suggesting that alkaline conditions and base cation accumulation significantly inhibit SOC sequestration. SiO_2 and Al_2O_3 show very weak correlations with SOC, indicating limited direct regulatory effects; instead, they indirectly influence SOC stability mainly by participating in the formation of soil mineral frameworks.

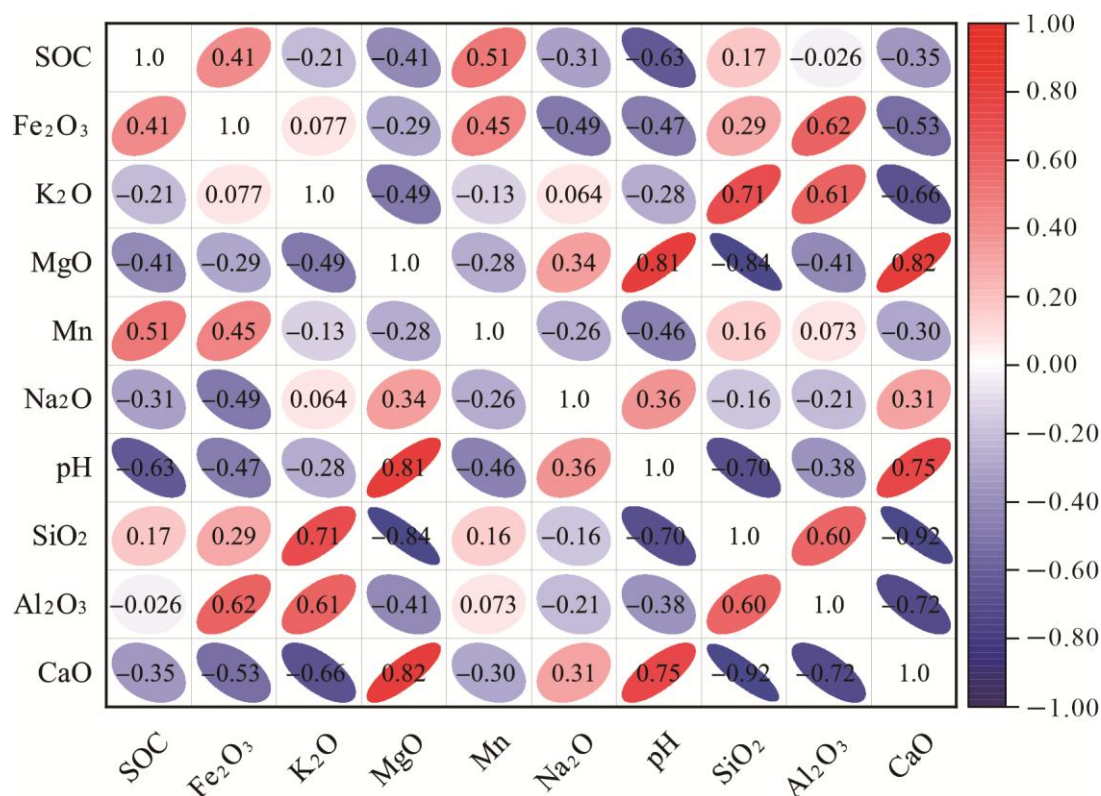


Figure 4. Correlation matrix between soil SOC and geochemical elements: SOC: soil organic carbon; SiO_2 : silicon dioxide; Al_2O_3 : aluminum oxide; Fe_2O_3 : iron (III) oxide; Mn: manganese; K_2O : potassium oxide; Na_2O : sodium oxide; CaO : calcium oxide; MgO : magnesium oxide.

PCA was performed on eight major elements and pH to reduce dimensionality and resolve core compositional features. The first three principal components (PCs) explain 83.02% of the total variance (Figure 5) and effectively represent the basin's overall soil geochemical characteristics. PC1 accounts for 52.94% of the variance and serves as the core component driving geochemical differentiation. It shows positive loadings on SiO_2 , Al_2O_3 , Fe_2O_3 , and K_2O , and negative loadings on CaO , MgO , and pH, clearly reflecting an opposing gradient between the "Si–Al–Fe oxide system" and the "base–alkaline system" across the basin, which is closely related to SOC spatial differentiation. PC2 explains 18.86% of the variance, characterized by positive loadings on K_2O and Na_2O and negative loadings on Mn, reflecting spatial differentiation between alkali metals and Mn. PC3 explains 11.22% of the variance, with positive loadings on Al_2O_3 and Fe_2O_3 , further emphasizing the central role of Fe–Al oxides in soil geochemical properties.

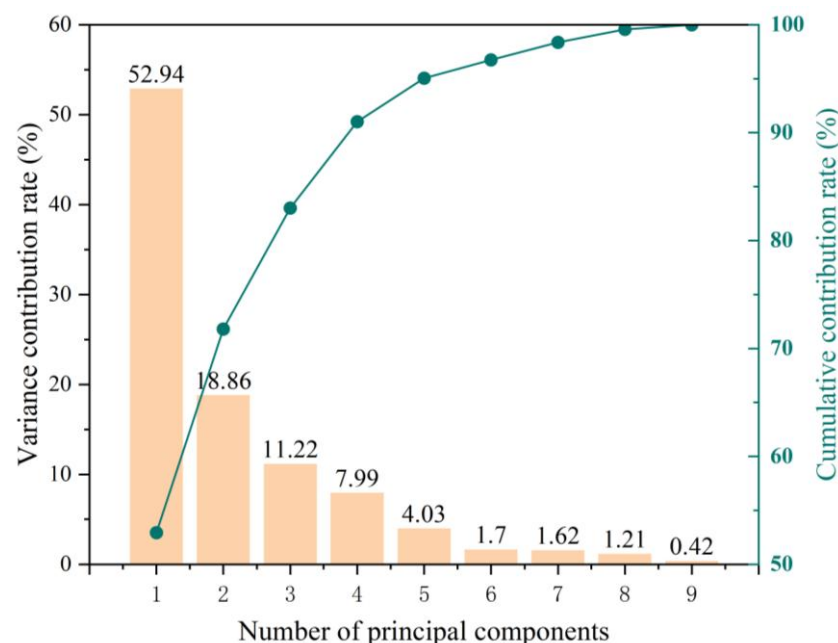


Figure 5. Diagram of principal component variance contribution rate and cumulative contribution rate.

The PCA loading heatmap (Figure 6) details indicator contributions: positive loadings of SiO_2 (0.41), Al_2O_3 (0.34), Fe_2O_3 (0.28), and K_2O (0.29) on PC1 indicate enrichment in the eastern acidic zone. In contrast, negative loadings of CaO (−0.44), MgO (−0.39), Na_2O (−0.19), and pH (−0.38) indicate accumulation in the western alkaline zone. On PC2, positive loadings of K_2O (0.51) and Na_2O (0.45) and negative loading of Mn (−0.51) reflect inverse distributions of alkali metals and Mn in the western saline–alkali zone. On PC3, high positive loadings of Al_2O_3 (0.58) and Fe_2O_3 (0.49) further highlight the dominance of Fe–Al oxides in soil mineral composition.

Correlation analysis between PCs and SOC (Figure 7) shows that PC1 is positively correlated with SOC. At the same time, PC2 and PC3 are negatively correlated, indicating that geochemical environments dominated by the Si–Al–Fe oxide system favor SOC accumulation, whereas base–alkaline systems and alkali metal enrichment suppress SOC sequestration. Spatially, high PC1 scores occur in the eastern and central basin, corresponding to acidic Fe–Al-rich environments; low PC1 scores occur in the west and south, corresponding to alkaline base-rich environments. High PC2 scores cluster in the west and south, coinciding with salinized areas (Figure 8), further confirming the intrinsic link between geochemical indicators and SOC.

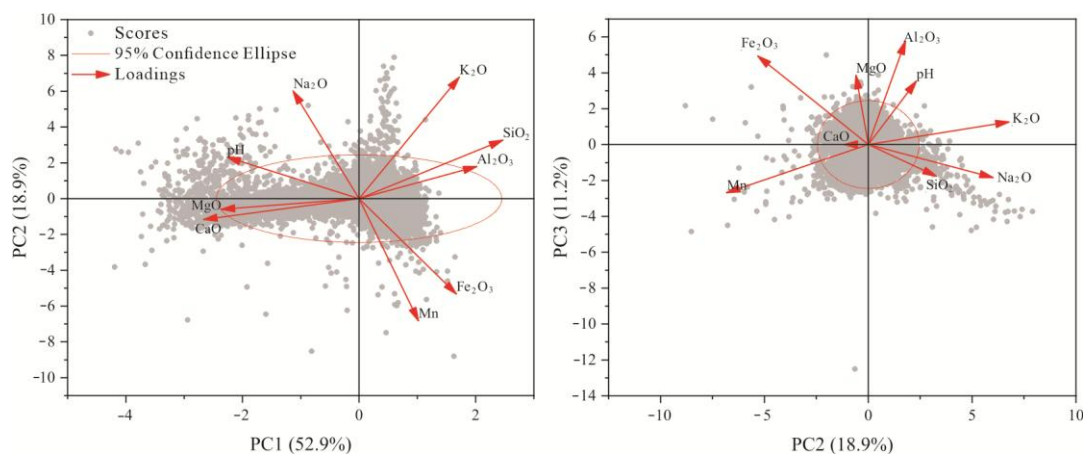


Figure 6. Principal component analysis score and loading plot: SiO₂: silicon dioxide; Al₂O₃: aluminum oxide; Fe₂O₃: iron (III) oxide; Mn: manganese; K₂O: potassium oxide; Na₂O: sodium oxide; CaO: calcium oxide; MgO: magnesium oxide.

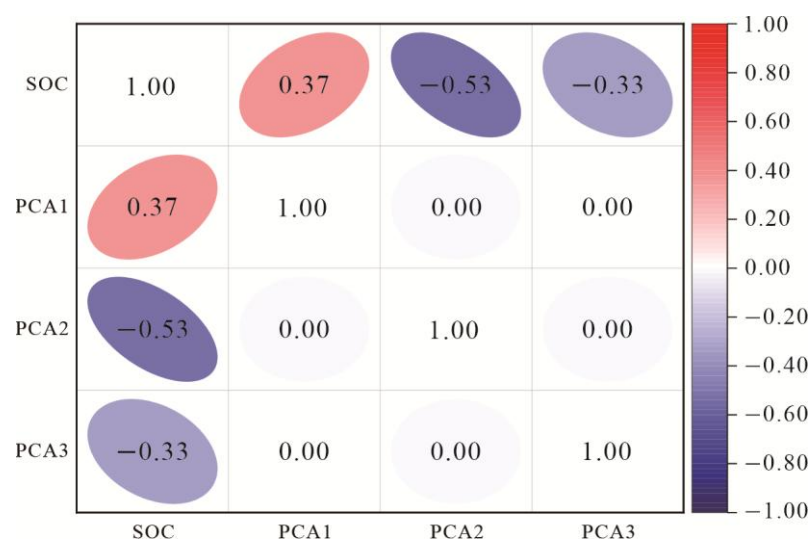


Figure 7. Correlation matrix between principal components and SOC.

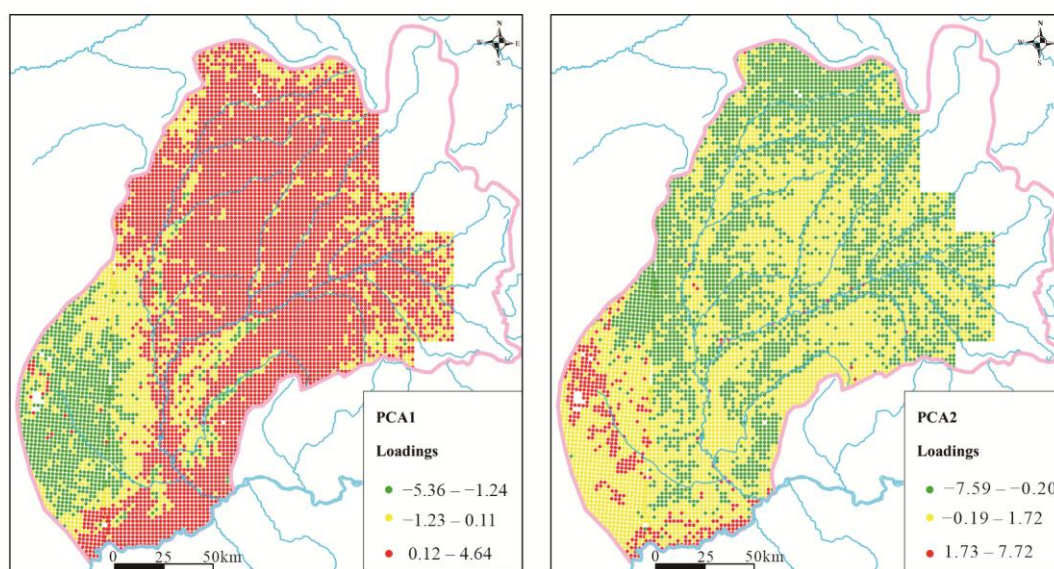


Figure 8. Spatial distribution map of principal component scores of soil samples. The pink line represents the scope of the Hulan River Basin.

3.3. Soil Geochemical Zoning and SOC Differences Among Zones

Based on the first three PCs, K-means clustering was used for geochemical zoning, and the silhouette coefficient identified five optimal zones. The Hulan River Basin was thus divided into five zones with significant differences in geochemistry ($p < 0.01$). Element concentrations differ markedly among zones (Figure 9), reflecting distinct parent materials and pedogenic processes.

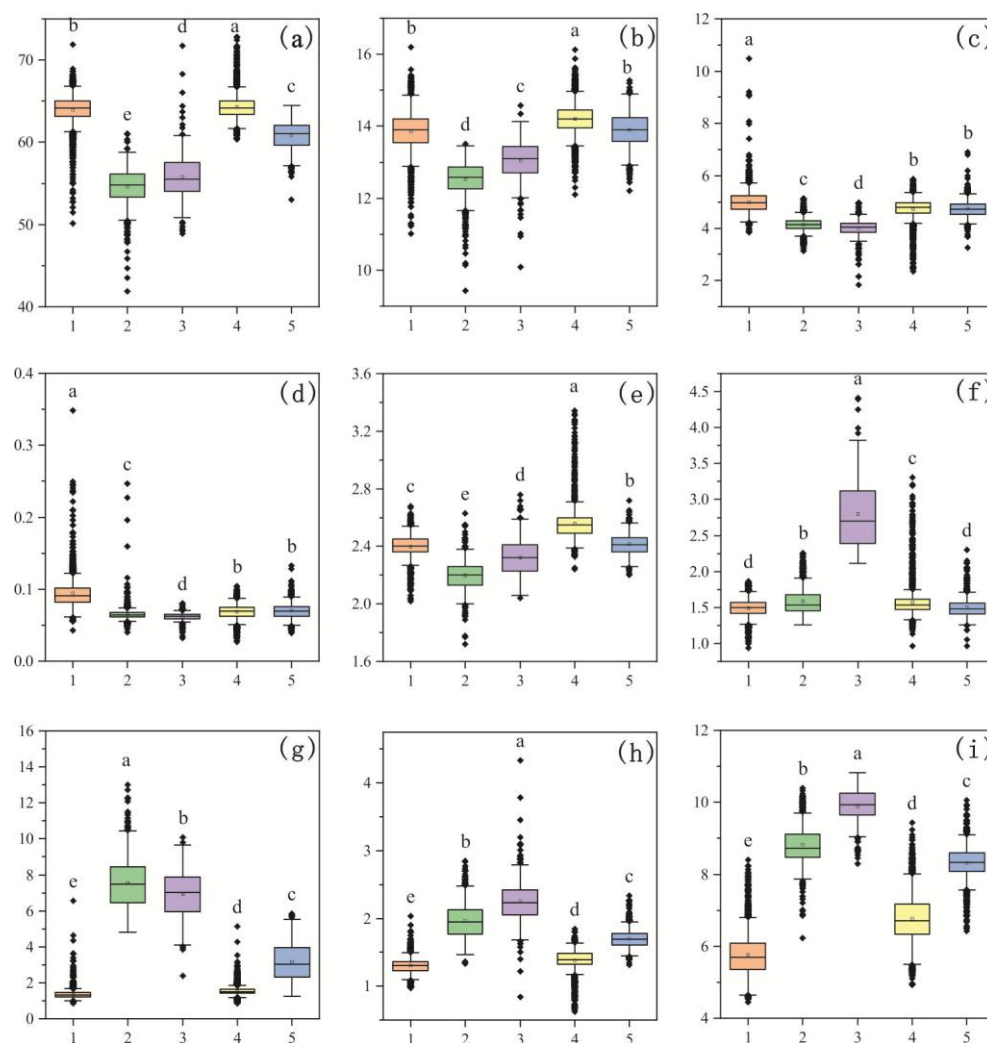


Figure 9. Boxplot of element content characteristics in each zone: (a) silicon dioxide (SiO₂); (b) aluminum oxide (Al₂O₃); (c) iron (III) oxide (Fe₂O₃); (d) manganese (Mn); (e) potassium oxide (K₂O); (f) sodium oxide (Na₂O); (g) calcium oxide (CaO); (h) magnesium oxide (MgO); (i) pH. pH is dimensionless; other units are %. Different lowercase letters (a, b, c, d, e) above each box indicate significant differences among groups at $p < 0.05$ based on one-way analysis of variance (ANOVA). Each box represents the interquartile range (IQR, 25th–75th percentile); the horizontal line inside the box is the median value.

Zone 1 (Strongly acidic residual-slope parent material zone): Mainly in the northeastern basin, characterized by high Fe₂O₃ and Mn, low pH, and low base cations.

Zone 2 (Ca–Mg-rich weakly alkaline alluvial parent material zone): In the western basin, with high CaO and MgO and weakly alkaline pH.

Zone 3 (Na–Mg-rich strongly alkaline saline–alkali alluvial parent material zone): Concentrated in western lowlands, with extremely high Na₂O and MgO, strongly alkaline pH, and marked salinization.

Zone 4 (Si–K-rich moderately acidic diluvial–alluvial parent material zone): The most extensive zone, with high SiO₂ and K₂O and moderately acidic pH.

Zone 5 (Ca–Mg-rich weakly alkaline aeolian loess parent material zone): In the central basin, with moderate CaO and MgO and weakly alkaline pH.

The spatial distribution of geochemical zones shows clear regional regularity (Figure 10), highly consistent with topographic and pedogenic differentiation of parent material, reflecting the co-evolution of “topography–parent material–geochemical properties”. SOC content differs extremely significantly among geochemical zones (ANOVA, $p < 0.01$)

(Figure 11), in the order: Zone 1 > Zone 4 > Zone 5 > Zone 2 > Zone 3. This demonstrates that geochemical background is a core intrinsic factor determining SOC spatial differentiation: acidic Fe–Al-rich environments favor SOC accumulation, while alkaline base-rich environments accelerate SOC decomposition, further validating correlation and PCA results.

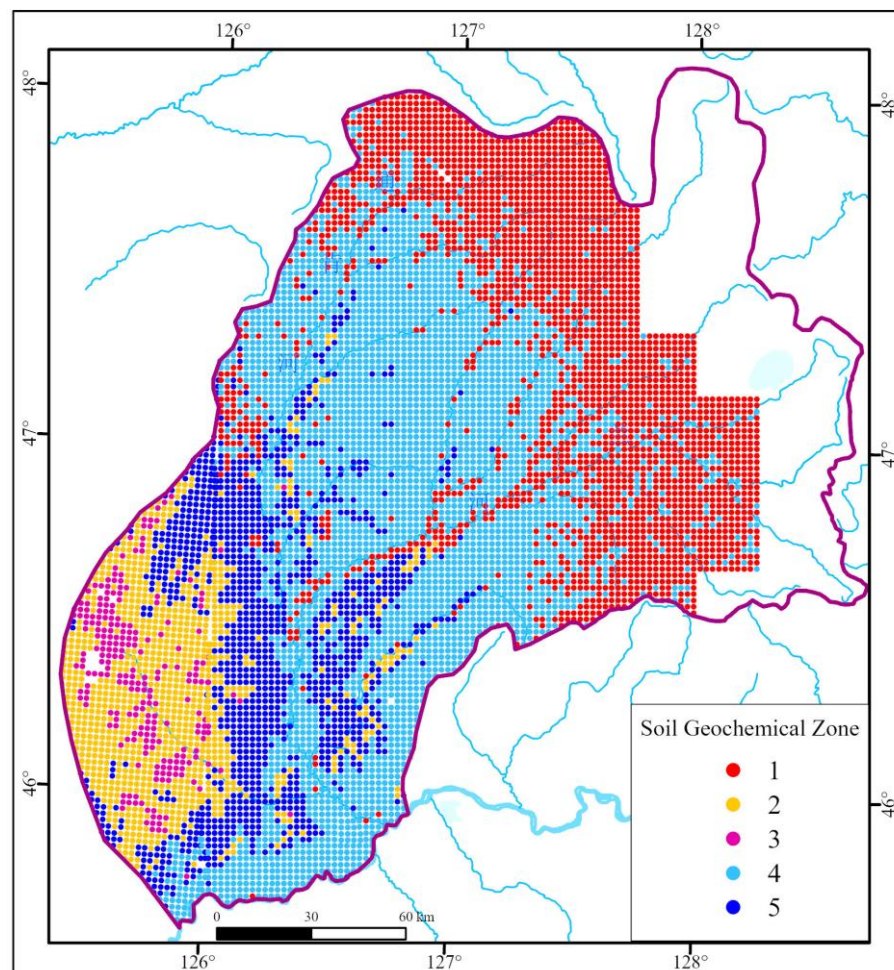


Figure 10. Soil geochemical zoning map of the Hulan River Basin. The pink line represents the scope of the Hulan River Basin.

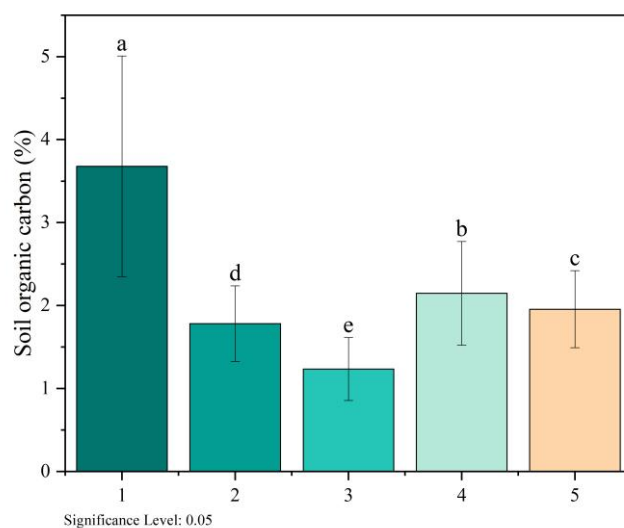


Figure 11. Soil organic carbon (SOC) content characteristics in different geochemical zones. Values with different lowercase letters (a, b, c, d, e) are significantly different at $p < 0.05$.

3.4. Analysis of Factors Influencing SOC Content Based on Geodetector

3.4.1. Factor Detector Results

The factor detector quantified the explanatory power (q -statistic) of environmental factors for SOC spatial differentiation (Figure 12), with the following order: aridity (Dry, $q = 0.57$) > mean annual temperature (TMP, $q = 0.50$) > geochemical zone (GZ, $q = 0.46$) > elevation (EL, $q = 0.41$) > net primary productivity (NPP, $q = 0.31$) > land use (LU, $q = 0.27$) > annual precipitation (PRE, $q = 0.23$) > soil type (ST, $q = 0.19$) > erosion intensity (EI, $q = 0.01$). Aridity, TMP, and GZ ($q > 0.4$) are dominant drivers; EL ($q = 0.41$) is an important driver; and EI ($q = 0.01$) has a negligible effect. This indicates that SOC spatial differentiation results from combined effects of climate, geochemical background, and topography, with climate (aridity, TMP) making the largest independent contribution and geochemical background exerting prominent intrinsic regulation.

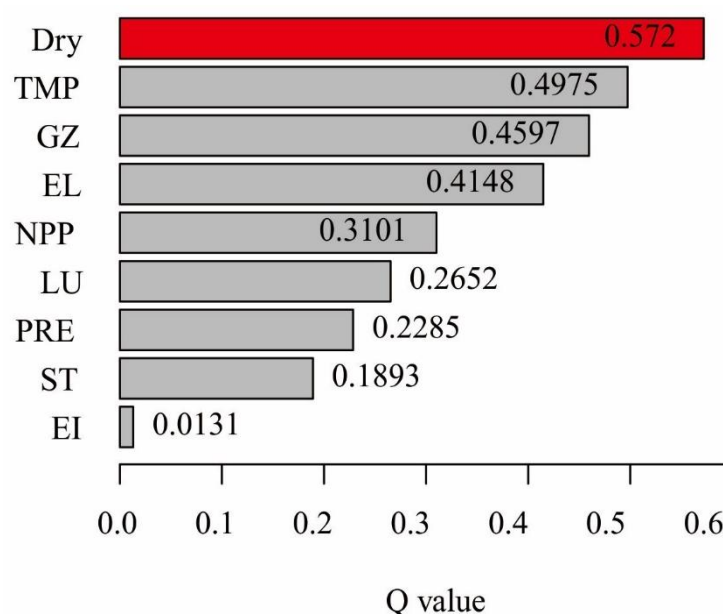


Figure 12. Results of the factor detector. Dry: aridity; TMP: mean annual temperature; GZ: geochemical zone; EL: elevation; NPP: net primary productivity; LU: land use; PRE: annual precipitation; ST: soil type; EI: erosion intensity.

3.4.2. Risk Detector Results

The risk detector clarified differences in SOC content among intervals of dominant factors (Figure 13). SOC decreases significantly linearly with rising TMP and aridity, and increases significantly linearly with rising PRE and elevation, consistent with hydrothermal regulation of SOC accumulation in black soil regions. NPP shows a clear threshold effect: SOC increases significantly when $NPP > 435 \text{ g C m}^{-2} \text{ yr}^{-1}$, indicating that sufficient organic matter input is a prerequisite for SOC accumulation. Forest and grassland have significantly higher SOC than cropland, reflecting SOC depletion by anthropogenic cultivation. Zones 1 and 4 have significantly higher SOC than other zones, confirming the protective effect of acidic Fe–Al-rich geochemical environments. Soil type and erosion intensity exert weak effects on SOC, consistent with factor detector results.

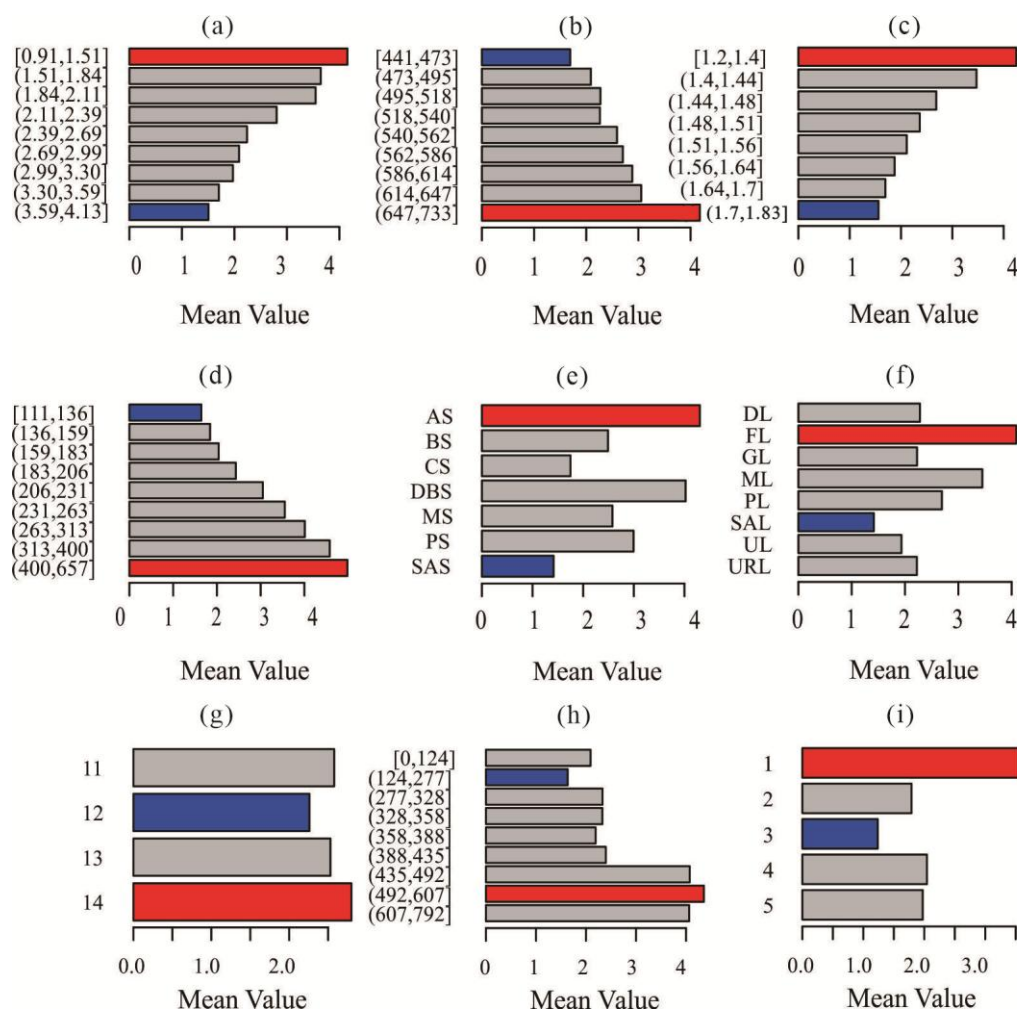
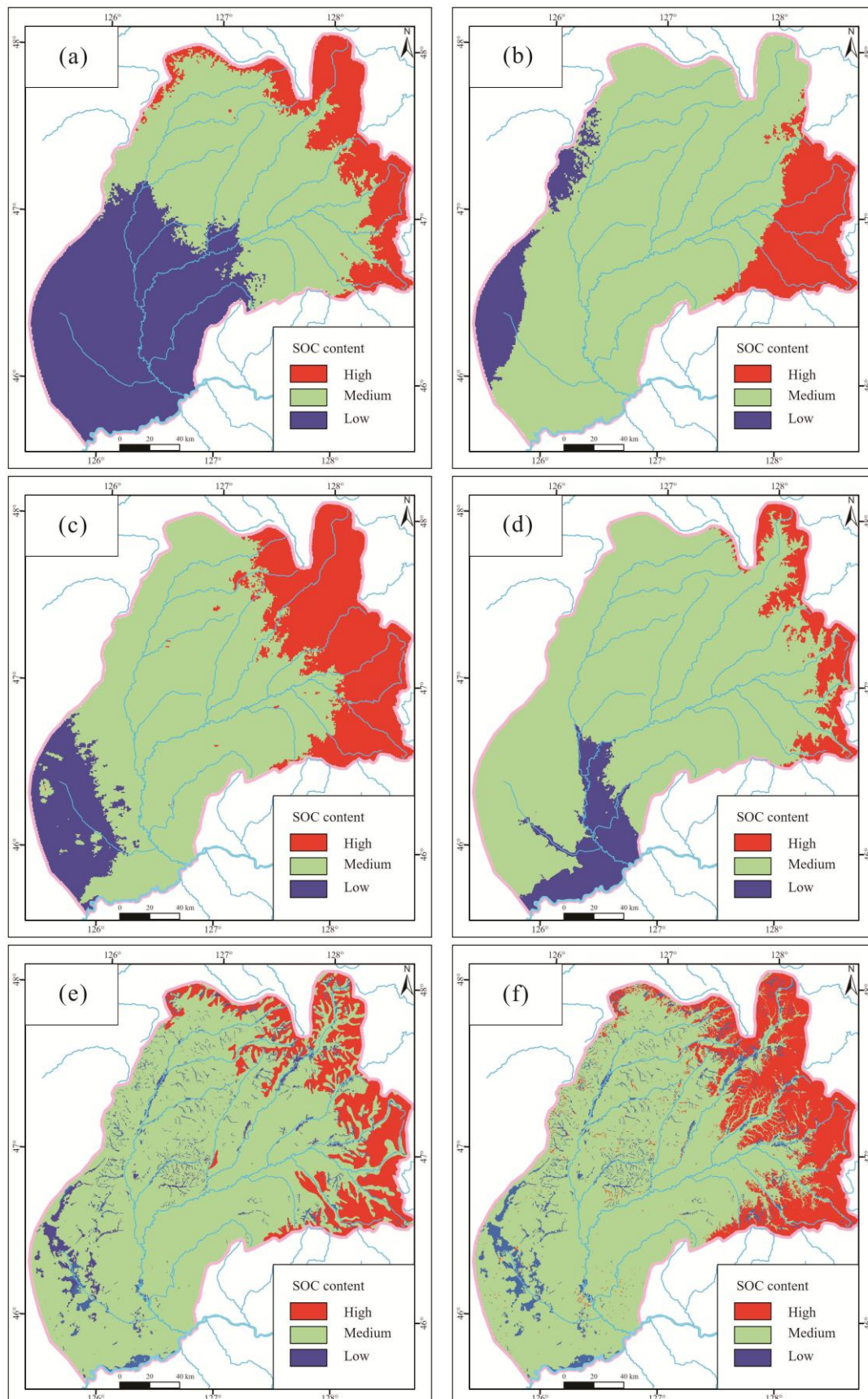


Figure 13. Results of the risk detector: (a) mean annual temperature (TMP); (b) annual precipitation (PRE); (c) aridity (Dry); (d) elevation (EL); (e) soil type (ST); (f) land use (LU); (g) erosion intensity (EI); (h) net primary productivity (NPP); (i) geochemical zone (GZ). Bars in red represent the maximum-value group, bars in blue represent the minimum-value group, and gray bars indicate intermediate-value groups.

3.4.3. Spatial Expression of Environmental Factor Effects

Spatial heterogeneity analysis of dominant environmental factors on SOC (Figure 14) shows that SOC high-value areas (red) cluster in the eastern basin, characterized by low aridity, low TMP, high elevation, high NPP, and corresponding to Zones 1 and 4 (acidic Fe–Al-rich environments). SOC low-value areas (blue) occur in the western basin, characterized by high aridity, high TMP, low elevation, and corresponding to Zones 2 and 3 (alkaline base-rich environments). This spatial coupling intuitively reveals multi-factor synergistic regulation of SOC patterns and provides spatial evidence for interaction analysis.



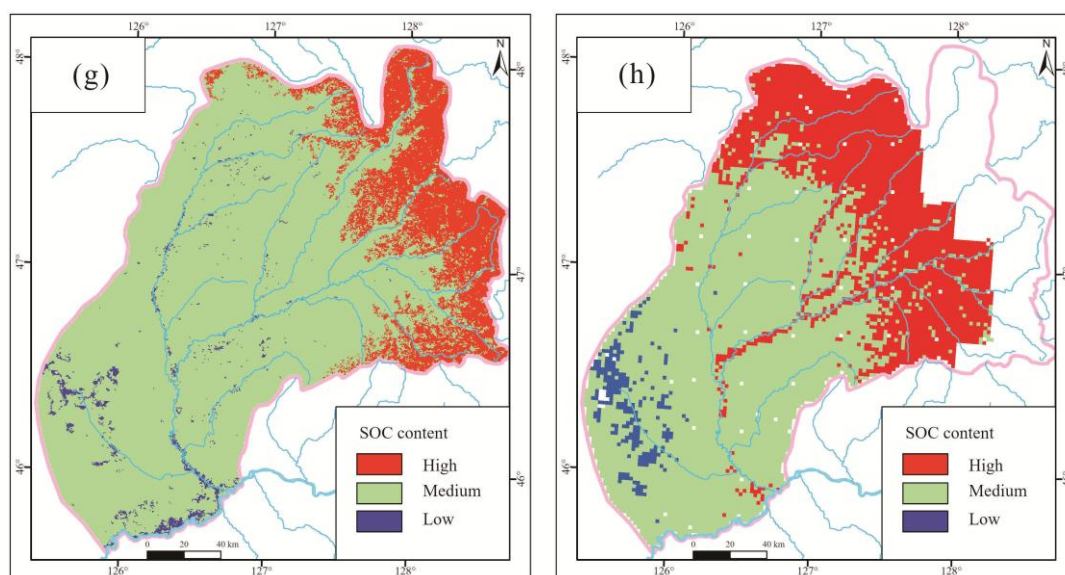


Figure 14. Spatial heterogeneity of the effects of different variables on SOC content: (a) mean annual temperature (TMP); (b) annual precipitation (PRE); (c) aridity (Dry); (d) elevation (EL); (e) soil type (ST); (f) land use (LU); (g) net primary productivity (NPP); (h) geochemical zone (GZ). The pink line represents the scope of the Hulan River Basin.

3.4.4. Interaction Detector Results

The interaction detector revealed synergistic effects of environmental factor pairs on SOC spatial differentiation (Figure 15). All two-factor interactions were enhancing (no antagonism), including non-linear enhancement (interaction $q > \text{sum of individual } q$) and bi-factor enhancement (interaction $q > \text{maximum individual } q$ but $< \text{sum}$). The interaction between GZ and Dry was strongest ($q = 0.63$), significantly exceeding their individual sum, indicating that synergy between geochemical background and aridity is key to shaping SOC patterns. Interactions between GZ and TMP or EL were also strong ($q > 0.55$), highlighting the modification of climatic and topographic effects by geochemical background. This confirms that SOC spatial differentiation is not controlled by a single factor but by non-linear synergistic interactions among climate, topography, and the geochemical background, with the latter acting as a core mediator that regulates the effects of climate and topography. Such mediation aligns with recent findings in Northeast China's black soil region, where machine learning-based spatial modeling demonstrated that intrinsic soil properties interact strongly with climate variables to determine SOC trajectories over time [3].

Accordingly, targeted carbon sequestration and soil conservation measures should be formulated separately for each geochemical zone in future regional management. For arid geochemical zones with strong drought constraints, water regulation and organic material input should be prioritized to mitigate the joint limitation of geochemical matrix and aridity on SOC accumulation. For high-altitude and low-temperature geochemical zones, conservation tillage and vegetation restoration are recommended to offset the weak carbon fixation capacity caused by low temperature. This differentiated approach, grounded in the recognition of geochemical mediation, is consistent with broader principles emerging from spatiotemporal analyses of farmland SOC in complex terrains, which emphasize the necessity of context-specific management aligned with local biogeochemical realities [38]. Differentiated agricultural management schemes matched to geochemical background can effectively reduce regional SOC loss and stabilize soil carbon pools across the whole basin.

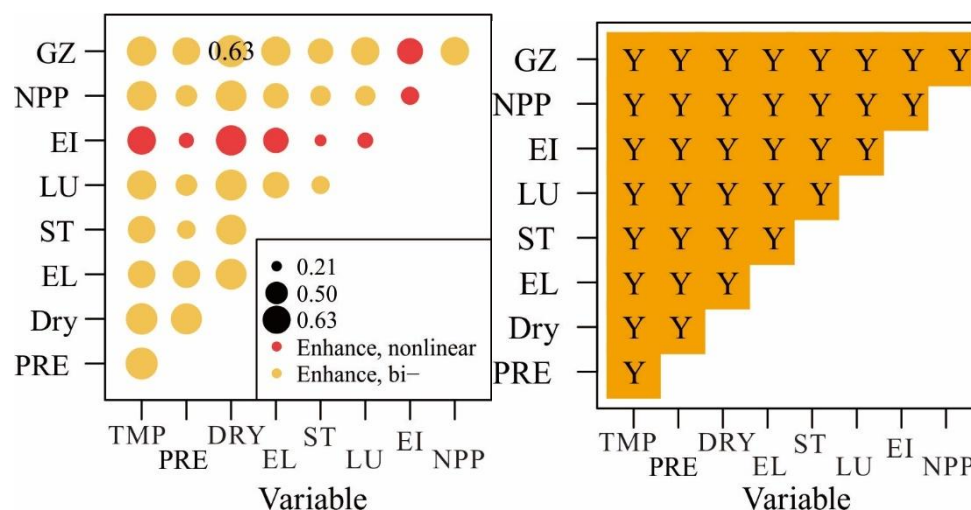


Figure 15. Results of the interaction detector. Dry: aridity; TMP: mean annual temperature; GZ: geochemical zone; EL: elevation; NPP: net primary productivity; LU: land use; PRE: annual precipitation; ST: soil type; EI: erosion intensity. Y indicates that the interaction between the two factors has a significant enhancing effect.

4. Discussion

4.1. Dominant Mechanisms of Soil Geochemical Properties Regulating SOC Sequestration

Surface soils in the Hulan River Basin exhibit typical aluminosilicate characteristics, with SiO_2 , Al_2O_3 , and Fe_2O_3 accounting for ~80% of the total elements, and geochemical indicators show strong spatial differentiation. CaO has an extremely high CV of 85%, and pH shows a bimodal distribution, creating coexisting acidic and alkaline zones that may directly shape SOC spatial patterns. Correlation and PCA results suggest that SOC is extremely significantly positively correlated with Fe_2O_3 and Mn ($r = 0.41, 0.51; p < 0.01$) and negatively correlated with pH, CaO, MgO, and Na₂O ($r = -0.63, -0.35, -0.41, -0.31; p < 0.01$). Combined with the opposing gradient between the Si–Al–Fe oxide system and base–alkaline system reflected by PC1, these observations imply that soil geochemical composition may act as a core intrinsic factor regulating SOC accumulation and decomposition, which can be summarized as a dual mechanism of “organo–mineral stabilization” and “saline–alkali stress-induced degradation” [13].

Strong positive correlations of Fe_2O_3 and Mn with SOC, together with their central loadings on PC1 and PC3, support the interpretation of an organo–mineral complexation mechanism mediated by Fe–Mn oxides [18]. This mechanism appears to be most pronounced in Zone 1 (northeastern strongly acidic residual-slope parent material zone), where intensive weathering tends to produce abundant amorphous Fe–Al oxides. With large specific surface areas and abundant hydroxyl groups, these oxides may form stable organo–mineral complexes with soil organic matter, potentially inhibiting SOC mineralization and decomposition as widely reported in previous studies [16–18]. This is consistent with the findings that Fe–Mn oxides enhance SOC persistence via adsorption and co-precipitation [39], which could explain why Zone 1 has the highest SOC.

In contrast, high pH and accumulation of Ca, Mg, and Na in western alkaline zones (Zones 2, 3) may represent major drivers of SOC degradation. The high CaO CV (0.85), its southwest enrichment, and the negative correlation with SOC appear to conflict with the report that Ca^{2+} promotes SOC accumulation in alkaline soils [40]. The discrepancy may arise from the unique high-pH, high-sodium environment in the western basin. Here, the flocculating effect of Ca^{2+} may be offset by the dispersing effect of Na^+ , limiting stable aggregate formation. High pH may promote the formation of unstable Ca–organic complexes with soluble organic matter and may stimulate microbial activity, thereby

accelerating SOC turnover [41]. Excess Na^+ can further disrupt soil aggregates [42], potentially exposing physically protected SOC to microbes and leading to rapid mineralization and loss [43], which may account for the lowest SOC in Zones 2 and 3. Rowley [19] systematically demonstrated pH-dependent regulation of Ca-mediated SOC stabilization: Ca-driven stabilization should dominate in alkaline soils ($\text{pH} > 7$), but excessive base cations may break Ca–organic matter bonds and weaken carbon sequestration, consistent with the negative CaO–SOC correlation observed here.

Notably, SiO_2 and Al_2O_3 show weak correlations with SOC, consistent with their uniform distribution ($\text{CV} < 0.10$) and high stability. They exert relatively limited direct control over SOC and may instead contribute indirectly to SOC stabilization by forming Si–Al–Fe mineral frameworks with Fe and Mn [44].

4.2. Synergistic Shaping of SOC Spatial Heterogeneity by Multi-Factor Interactions

Geodetector results show that aridity ($q = 0.57$), TMP ($q = 0.50$), and GZ ($q = 0.46$) are dominant drivers of SOC spatial differentiation, and all two-factor interactions are enhancing. The non-linear interaction between GZ and Dry is strongest ($q = 0.63$), significantly exceeding the sum of individual effects. This suggests that SOC spatial patterns emerge from non-linear synergistic interactions among climate, topography, and geochemistry, rather than single-factor control, consistent with findings by Wang [45] in black soil regions of Northeast China.

At the single-factor level, aridity is the strongest driver, with an east-to-west gradient that matches the “east-high, west-low” SOC pattern. Risk detector results confirm that SOC decreases linearly with rising aridity, consistent with the general rule that aridity accelerates SOC decomposition [46]. However, interaction-detector results show that aridity effects are not uniform but strongly dependent on the geochemical background—a “same climate, different effects” pattern [9]. In eastern acidic Fe–Al-rich Zones 1 and 4, moderate aridity may suppress microbial activity and slow SOC decomposition, while Fe–Mn oxide complexation offsets drought stress. In western alkaline, base-rich Zones 2 and 3, identical aridity synergizes with high pH to concentrate salts, increase organic matter solubility, and accelerate SOC mineralization [29,34], which helps explain the GZ $\times$ Dry interaction’s strongest explanatory power.

Elevation ($q = 0.41$) is positively correlated with SOC and interacts significantly with GZ, refining the understanding of macro SOC patterns. Eastern high-elevation areas have favorable hydrothermal conditions (low temperature, low aridity) and acidic residual-slope parent materials, favoring Fe–Mn oxide formation and SOC stabilization [16,47]. Western low-elevation areas (Songhua River lowlands) have flat terrain, poor drainage, severe salinization, and high aridity and temperature stress, which may limit SOC accumulation and ultimately contribute to the “east-high, west-low” pattern. This aligns with Li’s findings on SOC distribution in Northeast China. These results further indicate that the geochemical background may act as an intrinsic mediator of topoclimatic effects, helping to fill gaps in understanding multi-factor coupling mechanisms.

Furthermore, the NPP threshold for SOC (significant increase above $435 \text{ g C m}^{-2} \text{ yr}^{-1}$) reflects potential synergy between biological input and geochemical environment: high NPP provides abundant organic matter [48], and acidic Fe–Al-rich zones (1, 4) may stabilize this input via mineral protection, supporting high SOC. Even with high NPP, alkaline saline–alkali zones (2, 3) may fail to effectively sequester SOC due to aggregate disruption and enhanced microbial activity, providing additional evidence for the role of geochemical regulation.

Land use and human activities also appear to play an important role in SOC spatial differentiation. Forestland and grassland exhibited significantly higher SOC content than cropland, likely due to long-term organic matter input and less disturbance. Intensive

cultivation, tillage, and long-term agricultural utilization may reduce soil aggregation stability and accelerate SOC mineralization. Anthropogenic activities may further regulate SOC storage by interacting with geochemical background: in acidic geochemical zones, vegetation restoration helped maintain high SOC; in alkaline saline–alkali zones, agricultural practices exacerbated SOC loss. These effects demonstrate that anthropogenic factors should not be ignored when revealing SOC spatial heterogeneity.

4.3. Limitations and Future Prospects

One limitation of this work is that this study focuses only on surface soils (0–20 cm), excluding subsoil (>20 cm) SOC characteristics. Subsoil SOC accounts for >40% of total black soil carbon pools [49], and its drivers may differ markedly (e.g., mineral forms, organic matter input pathways), reducing the completeness of regional carbon pool assessment [50].

XRF analysis measured total major elements but did not distinguish between specific Fe–Al oxide phases (crystalline vs. amorphous). The inferred Fe–Mn oxide stabilization mechanism relies on total-element correlations and lacks direct microscale evidence; the efficiency differences among oxide phases remain unclear [44].

It does not quantify anthropogenic activities (e.g., tillage intensity, fertilization rate). Given the high proportion of cropland, human impacts on SOC are substantial and may confound geochemical vs. anthropogenic drivers, reducing mechanistic precision.

5. Conclusions

This study demonstrates that soil geochemical background is the primary intrinsic control on SOC spatial differentiation in the Hulan River Basin, surpassing traditional climatic and topographic factors in explanatory power. The non-linear synergy between geochemical zones and aridity critically modulates climatic effects on SOC, producing contrasting SOC responses under similar climatic conditions.

Mechanistically, SOC preservation is governed by a dual pathway: organo–mineral complexation with Fe–Mn oxides enhances carbon stabilization, whereas high pH and exchangeable base cations (Ca, Mg, Na) promote aggregate disruption and mineralization—with sodium specifically offsetting the flocculation effect of calcium.

The geochemical zoning framework developed here provides a more mechanistically grounded alternative to conventional soil classification systems for regional carbon stock assessment. This approach enables targeted, zone-specific carbon management strategies—protecting high-carbon zones, improving low-carbon ones, and optimizing medium-carbon areas—offering a practical pathway for enhancing soil carbon sinks and sustaining black-soil quality in Northeast China.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18157765/s1>, Figure S1: Optimization process of continuous variable discretization methods; Figure S2: Results of continuous variable discretization.

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