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Soil mosaic: A multi-modelling approach to understand the complex interactions that determine the spatial heterogeneity of soil health – An example from Serbia ☆

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ABSTRACT

In this study, an integrated and explainable modelling framework is applied to assess soil health and its spatial heterogeneity in Eastern Serbia. The approach combines Network Analysis (NA), Self-Organizing Maps (SOM) and the Geodetector Model (GDM) to identify key soil indicators, reveal spatial patterns and quantify the influence of environmental factors. The main objectives were: (i) to develop a scalable and transferable methodology to assess soil health, (ii) to identify the most influential natural and anthropogenic factors and (iii) to create a Soil Health Disturbance Index (SHDI) to visualise the impact at ecosystem level. A total of 2,555 soil samples were analysed using fourteen key indicators, while nine environmental variables were considered as potential influencing factors. The network analysis identified pH, cadmium (Cd) and potassium (K) as the most central elements within the soil system. SOM clustering revealed five different spatial patterns associated with dominant soil processes, while GDM results emphasised soil type ($Q = 0.26$) and parent material ($Q = 0.24$) as the strongest individual influencing factors. In particular, interactive effects such as soil type ∩ soil erosion ($Q = 0.47$) indicated a significant nonlinear amplification of soil health disturbances. The SHDI results showed that 26.9 % of the region is categorised as highly disturbed, mainly in urban and industrial areas. Overall, the proposed framework enhances the diagnostic capacity for soil health assessment and offers practical support for sustainable soil management and evidence-based spatial planning.

1. Introduction

Soil health (SH) is a modern framework developed over decades of research to identify the key characteristics of highly functional soils (Wood and Blankinship, 2022). It is defined as the sustainable ability of soil to function as a dynamic and living ecosystem that supports plants, animals and people (USDA-NRCS, 2023). At the same time, this concept serves as an important link between agricultural practises, soil science, policy decisions, stakeholder priorities and sustainable supply chain management (Kadović et al., 2016; Lehmann et al., 2020). There is a broad global consensus that maintaining soil health is critical for human sustainability and environmental resilience (Belanović Simić, 2017; Bünemann et al., 2018). A standardised and robust framework for soil health assessment and management is therefore essential to achieve long-term ecological balance (Rinot et al., 2019).

This concept thus emphasises the importance of soil as a provider of essential ecosystem services, which requires a multidisciplinary approach and comprehensive assessment methods (Zhao and Wu, 2021). Although the concept of soil health is increasingly recognised in scientific and professional discussions, its practical implementation still faces significant methodological challenges (Bünemann et al., 2018; Nath et al., 2024; Celis et al., 2024). Various methods for assessing soil health have been developed worldwide, based on different aggregation techniques and indicator sets (Drobnik et al., 2018). However, there is a clear need for further refinement and standardisation of these methods in order to effectively integrate and optimise the indicators.

Addressing these challenges is critical to transforming theoretical frameworks into actionable strategies to tackle the problems of global

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food security and environmental sustainability. For example, standardisation of methodology would improve the scientific reliability and universal applicability of soil health assessments (Bünemann et al, 2018; EC, 2020; AbdelRahman et al, 2019; Hitzfeld et al, 2024; de Paul Obade and Lal, 2016; Lichtenberg, 2024; Perović et al, 2025). Recent reviews also suggest that more attention should be paid to understanding what soil indicators tell us about soil functioning and the associated risks or problems (Fan et al., 2025).

In this regard, the application of the Soil Health Index (SHI) provides a robust framework for synthesising multidimensional soil health data into a single, integrative metric (Stevens, 2018). This assessment approach builds on the widely recognised three-phase framework for soil quality assessment and integrates both quantitative and qualitative aspects to ensure a context-specific and multidimensional interpretation of soil condition (Andrews et al., 2004; Doran and Parkin, 1994). In the initial phase, a set of relevant indicators that best represent the soil condition of the study area is systematically selected to form the total data set (TDS). These indicators should cover a wide range of physical, chemical and biological soil properties to ensure a holistic assessment of soil health (Frost et al., 2019). Importantly, the selection of the most appropriate indicators is also influenced by site-specific factors, as the local context plays a crucial role in determining which indicators are most representative (Aqdam et al., 2023). Multiple indicators are essential for assessing soil health, as no single parameter can fully capture the complex characteristics of soil or identify problems that affect its fertility and sustainability (Guo, 2021). For example, research by Lehmann et al. (2020) shows that 65 % of soil health studies include key indicators such as organic matter (OM), pH and plant-available concentrations of phosphorus (P) and potassium (K). However, several authors emphasise that the widespread reliance on chemical indicators may underrepresent biological and structural soil functions that are critical to ecosystem resilience (Fan et al., 2025; Derakhshan-Babaei et al., 2021).

In the second phase, the selected indicators are evaluated to determine their relative importance, including the calculation of weighting coefficients. In this phase, statistical methods such as correlation and multivariate analyses are often used to determine the indicators that contribute most to the final result. Despite their widespread use, recent studies indicate that the selection and weighting of indicators is often influenced by subjective decisions, potentially limiting the reproducibility and comparability of SHI scores between regions (Bünemann et al., 2018; Fan et al., 2025).

In the third and final phase, all selected and appropriately weighted indicators are integrated into a single Soil Health Index (SHI), which provides a comprehensive and quantitative representation of overall soil health. This integrative approach improves our understanding of the inherent complexity of soil systems and serves as a fundamental tool to inform sustainable soil management practises (Fausak et al., 2024). However, as Derakhshan-Babaei et al. (2021), Mirghaed and Souri (2022) and Alogaidi et al. (2025) point out, integration often fails to adequately account for spatial heterogeneity and landscape configuration, factors that can exert a significant influence on the spatial distribution and interpretation of soil health indicators.

The reliability of the SHI essentially depends on its ability to accurately capture the spatial and temporal heterogeneity of soils. Therefore, its application to large geographical units such as regions or entire countries is crucial for strategic decisions to ensure long-term sustainable management of soil resources (Rinot et al., 2019). As Berhe (2019) points out, the factors influencing soil health heterogeneity are complex and originate from both natural processes such as geological dynamics, climate change and erosion by water and wind, as well as anthropogenic activities. Intensive agricultural practises, for example, contribute to soil degradation by depleting OM and reducing water retention capacity. Similarly, industrial activities, urbanisation and deforestation pose significant threats to soil health as they introduce potentially toxic elements (PTE), organic pollutants and other hazardous substances into the soil system (Pavlović et al., 2021; Saljnikov et al., 2019). Since soil health is influenced by both natural and antopogenic factors, which can vary greatly from region to region, it is important to assess not only their individual impacts, but also their interactions and relative intensity (Qiao et al., 2022; Lu et al., 2024).

A wide range of methods have been used to investigate the multiple processes influencing soil health, including classical and multivariate statistical analyses, receptor models, machine learning techniques, multiple criteria decision making (MCDM) approaches and advanced spatial analysis methods. Each of these approaches provides unique and complementary insights into the complex interactions that influence soil functioning at different scales (Saha et al, 2024; Čakmak et al, 2023; Fathizad et al, 2020; Paul et al, 2020; Nabiollahi et al, 2018; Rossiter, 2021; Kaya and Dengiz, 2024; Sarğın et al, 2024). Recent studies have also emphasised the value of spatial analysis techniques such as hot-spot and cold-spot analyses and landscape metrics, including patch density, aggregation and dominance, in revealing spatial patterns of soil variability at the regional scale (Mirghaed and Souri, 2022; Derakhshan-Babaei et al., 2021). In addition, the integration of Digital Elevation Model (DEM) and remote sensing-derived indicators has significantly improved the capability for large-scale soil health assessment and spatial modelling. However, the reliability of these approaches depends on careful calibration with soil data, and they may have limited capacity to directly represent specific soil functions (Aqdam et al., 2023).

Among the emerging tools in soil science, network analysis (NA) has recently attracted attention due to its ability to capture and interpret the intricate structural and functional relationships within soil ecosystems. By conceptualising soil components and processes as interconnected networks, NA provides a novel and powerful framework for investigating the systemic properties of soil health that are often overlooked by conventional approaches (Matić et al, 2023; Martín-Sanz et al., 2022; Raiesi and Beheshti, 2022; Zahedifar, 2023). By visualising soil properties and processes as nodes and links in a network, researchers gain valuable insights into the structure, function and resilience of soil systems (Martín-Sanz et al., 2022; Raiesi and Beheshti, 2022; Zahedifar, 2023). In addition, self-organising maps (SOM), a type of artificial neural network, are particularly effective in unsupervised learning tasks and are well suited for visualising and interpreting high-dimensional soil data (Banerjee et al., 2023; Licen et al., 2023). In contrast, the geodetector model (GDM) is a statistical tool for recognising spatial heterogeneity and investigating relationships between variables at different spatial scales (Wang et al., 2010). In soil science, GDM has become a key tool for understanding the spatial variability of soil properties and their interactions with environmental factors (Tian et al., 2022; Perović et al., 2023; Gong et al., 2024).Although methods such as NA, SOM and GDM have been used individually in soil research, their combined application to assess soil health has not yet been sufficiently explored. This integration enables a more comprehensive assessment of soil health, facilitates the identification of key drivers and provides deeper insights into the complex processes that shape soil ecosystems.

In view of the context outlined above, the present study pursues the following objectives: (1) to develop a comprehensive and standardised methodological framework for soil health assessment based on samples from forestry and agriculture, (2) to analyse the individual soil health indices and identify their possible sources, (3) to identify and quantify key factors, both natural and anthropogenic, that are responsible for the spatial heterogeneity of soil health, with the aim of developing a flexible and practical model for a simplified assessment, and (4) the creation of a Soil Health Disturbance Index (SHDI) to map and interpret the impact of factors that influence the ability of soil to function as a resilient and active system.

In order to achieve the described objectives, this study utilises the database of the national project of the Ministry of Agriculture, Forestry and Water Management of the Republic of Serbia entitled “Control of soil fertility and determination of hazardous and harmful substances in the soils of the Republic of Serbia”. This project, carried out by the Soil

Institute in Belgrade, includes an extensive database of 2,555 soil samples and serves as a basis for improving the implementation of the United Nations Sustainable Development Goals (SDGs) in Serbia. This research provides an original scientific contribution through the development of an innovative integrated framework (NA-SOM-GDM) and the novel Soil Health Disturbance Index (SHDI) to quantitatively assess the synergistic impacts of natural and anthropogenic factors on soil health, enabling precise mapping of spatial heterogeneity and identification of critical intervention points. The results are expected to significantly improve the understanding of soil health and its complex interactions and provide valuable insights for the development of effective prevention strategies and sustainable soil management practises that support long-term environmental protection.

2. Materials and methods

2.1. Study areas

Eastern Serbia covers an area of 29,487 km^2, stretching east from Belgrade and central Serbia to the borders with Romania, Bulgaria and North Macedonia (Fig. 1). The Danube and Timok rivers delimit the northern and eastern borders of the study area, while the southern regions merge into the districts of Pčinja and Jablanica. The major rivers, including the Danube, Nišava, Pčinja and South Morava, characterise the landscape and climate of the region and connect it with Central Europe and the Balkan Peninsula.

The study covers ten statistical regions of Serbia, which are defined by the country's official administrative units: Belgrade, Podunavlje, Braničevo, Bor, Zaječar, Nišava, Pirot, Toplica, Jablanica and Pčinja (Fig. 1). Belgrade, the capital of Serbia and an economic centre, has developed sectors such as services, trade and finance. The regions of Bor and Zaječar are known for their mining industry, especially copper and gold mining in Bor, which contributes significantly to Serbia's industrial GDP. Nišava, with the city of Niš, is characterised by the electronics, technology and medicine sectors, while the Toplica and Jablanica regions are focused on agriculture and food production. The climate in eastern Serbia is predominantly continental, with warm summers and cold winters, with regional differences due to the diverse geography. The Danube basin has a temperate continental climate with moderate rainfall, with an average annual temperature of around 11–12 °C and annual precipitation of about 590–650 mm. In contrast, the Nišava and Toplica regions benefit from milder conditions due to their river valleys; Niš has an average annual temperature of 11.8 °C and receives about 607 mm of precipitation, while the Toplica region (e.g. Prokuplje and Kuršumlija) records 10.5–11.2 °C and about 700 mm of precipitation annually. Mountainous regions such as the Stara Planina and Suva Planina mountain ranges in the Pirot and Bor regions have harsher winters with significant snowfall, offering opportunities for winter sports. Topographically, eastern Serbia is very diverse, ranging from the fertile plains of the Danube and the valleys of the Braničevo region to the towering mountain ranges of Bor, Pirot and Zaječar. The mountain ranges, including Stara Planina (with its highest peak Midžor at 2,169 m), Rtanj (Šiljak peak at 1,565 m) and Suva Planina (Trem peak at 1,810 m), offer breathtaking landscapes and are ideal for tourism, especially for hiking. Agriculture is the most important economic sector in many parts of eastern Serbia, especially in the fertile valleys of the Morava River and the Danube basin. The Podunavlje and Jablanica regions are known for fruit growing (plums, apples, pears), viticulture, vegetable growing and grain production. In Toplica and Nišava, the cultivation of medicinal plants and arable crops has a long tradition. Livestock farming is particularly widespread in the hilly and mountainous regions, where extensive grazing areas are available. Eastern Serbia is characterised by marked demographic contrasts. While larger cities such as Belgrade, Niš and Leskovac are experiencing population growth, smaller towns and villages are struggling with significant depopulation. Young people are increasingly migrating to urban centres, especially Belgrade, in search of better living conditions and employment opportunities. This trend, combined with an ageing population, is particularly pronounced in mountainous regions and leads to development imbalances and numerous socio-economic challenges (Manojlović et al., 2018).

2.2. Multi-modelling approach

In this study, a comprehensive methodological framework called NA-SOM-GDM was developed to accurately assess soil health and analyse the influence of various anthropogenic and natural factors on its spatial heterogeneity (Fig. 2). The framework is divided into three distinct phases, each utilising advanced techniques to uncover and quantify the complex dynamics of soil health.

The first phase utilised NA, an advanced statistical approach to

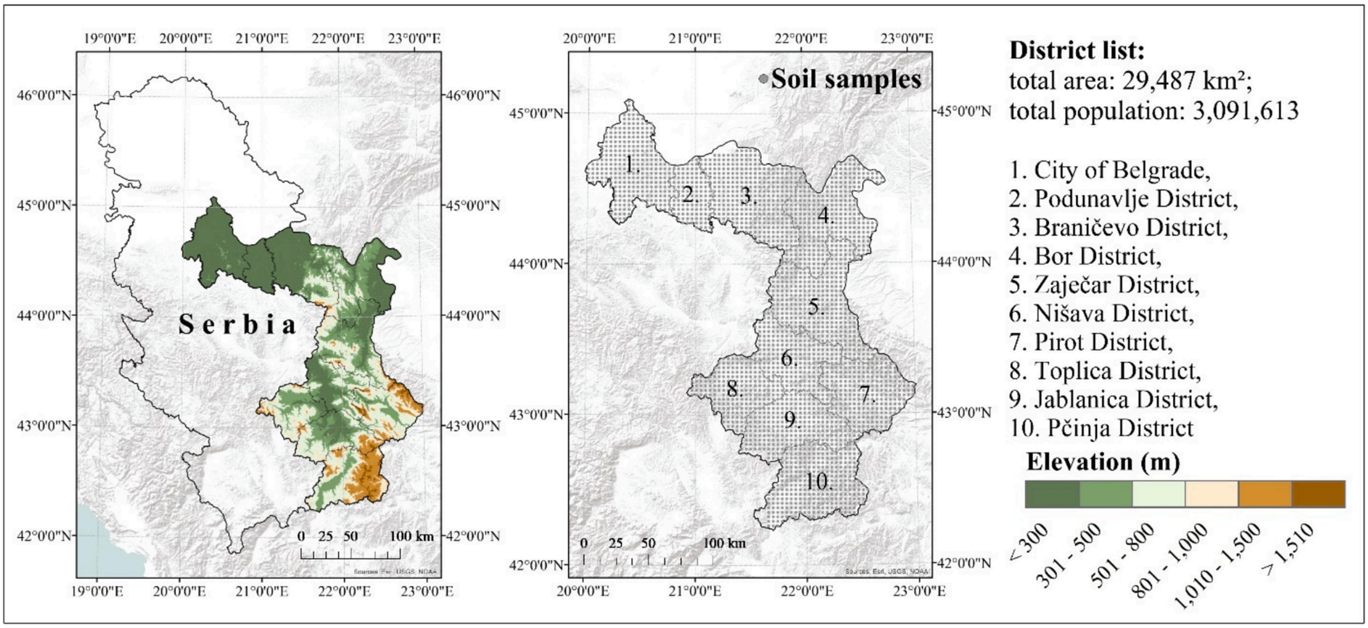

Fig. 1. Location of the study area.

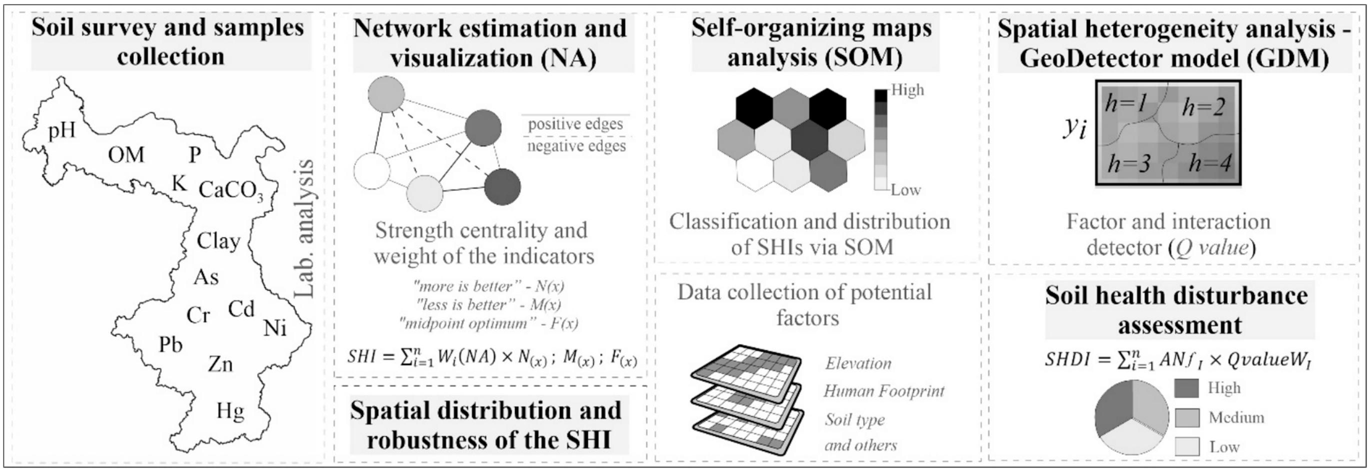

Fig. 2. Flowchart of the proposed methodology (NA-SOM-GDM).

identify and quantify complex, multidirectional interactions between soil health indicators. This technique uncovered critical relationships between key indicators and provided precise measurements of the intensity and strength of their connections. By visualising these relationships, NA enabled a clearer understanding of the systemic dynamics that determine soil health. The second phase applied the SOM model, a machine learning method particularly suited for detailed spatial analysis and classification of data. SOM enabled the identification of specific spatial patterns of individual soil health indices, which were then grouped using the k-means clustering algorithm. This methodological step enabled the delineation of key spatial clusters that provide a nuanced understanding of the structural characteristics of the SHI. By facilitating a detailed examination of spatial variations, SOM has significantly improved the interpretability of soil health data. The final phase utilised the GDM, a statistical method for investigating complex interactions between factors affecting soil health. GDM enabled the disentanglement of individual and interactive effects of these factors, improving the understanding of their contributions to the spatial heterogeneity of SHI. This analysis provided crucial insights into the underlying mechanisms of soil health variability and highlighted the synergistic and independent roles of natural and anthropogenic influences. A notable innovation of this framework is the development of a quantitative index that allows a detailed spatial analysis of the impact of critical drivers on soil health. This index is a valuable tool for accurate assessment and effective management of soil health that addresses the challenges posed by both human activities and natural processes.

2.2.1. *Soil analysis for comprehensive assessment of soil health*

A total of 2555 soil samples (0–30 cm) were taken from the study area (Fig. 1), using a systematic sampling pattern with regular spacing to ensure even spatial coverage of the region. The following physical and chemical soil properties were analysed in the laboratory: clay content was determined by the pipette method modified according to the International B method (Gee and Or, 2002), soil organic matter (OM) by dry combustion according to SRPS ISO 10694 and pH (KCl) according to SRPS ISO 10390. Available P and K were determined using the Al-method of Egner-Riehm (Enger and Riehm, 1958). The total content of arsenic (As), cadmium (Cd), chromium (Cr), copper (Cu), mercury (Hg), nickel (Ni), lead (Pb) and zinc (Zn) in the soil samples were measured by digestion in aqua regia (SRPS ISO 11466) and determined on an ICAP 6300 optical emission spectrometer (Thermo Electron Corporation, Cambridge, UK). Lower limits of detection for the elements were: 0.6436 (As), 0.0166 (Cd), 0.2897 (Cr), 2.3233 (Cu), 0.2239 (Ni), 2.8597 (Pb), 8.5106 (Zn), and 0.017 mg/kg (Hg). For verification of the results, a reference soil material (ERM-CC141 loam soil, Belgium).

2.2.2. *Data collection of potential factors*

Based on a thorough review of the relevant literature and specific research conditions (Jakovljević et al., 1997; Mrvić et al., 2013, 2009; Manojlović et al., 2017; Pavlović et al., 2017), we identified nine natural and anthropogenic factors that significantly influence the spatial heterogeneity of soil health (Fig. S1). The geological characteristics of the study area were analysed using soil parent material (SP) data at 1:500,000 scale obtained from the Geological Information System of Serbia (https://geoliss.mre.gov.rs/). In order to gain a detailed understanding of the soil types (ST) that are central to this study, we used a modified pedological map (Mrvić et al., 2013) provided by the Institute of Soil Science (https://www.soilinst.rs/). In addition, a 1:500,000 scale map based on the research of Lazarević (1983) was used to assess the impact of soil erosion (SE) on soil health. Land use (LU) data was derived from the Global Land Cover product for 2021 with a resolution of 10 m and developed using Sentinel-1 and Sentinel-2 satellite data (Zanaga et al., 2022). Topographic factors such as elevation (EL) and slope (SL) were extracted from the ASTER GDEM dataset, which provides a spatial resolution of 30 m. Landform (LF) classification was performed using the USGS Map of Global Ecological Land Units according to the methodology proposed by Hengl (2018). Data from the Human Footprint (HF) dataset was used to assess anthropogenic impacts. This dataset, developed by Mu et al. (2022), has a spatial resolution of 1 km and includes eight variables representing human pressure on the environment, e.g. built environments, population density, night-time lighting, cropland, pastureland, roads, railways and navigable waterways. Distance to industrial areas (DI) was assessed using data from the Serbian Environmental Protection Agency (SEPA, 2018), specifically its database of potentially contaminated sites.

The spatial distribution of all these factors is shown in Fig. S1 and provides a comprehensive overview of the natural and anthropogenic elements influencing soil health in the study area.

2.2.3. *Network estimation and visualization*

There are a variety of multivariate statistical approaches for deriving the weighting coefficients of soil health indicators. Among them, Principal Component Analysis (PCA) remains a widely accepted and robust technique for investigating the underlying structure, variability and sensitivity of soil health metrics (Yu et al., 2023; Zhang et al., 2022a). Recently, however, network analysis has proven to be a superior approach. In contrast to PCA, which focuses on identifying dominant trends, NA enables detailed modelling of complex relationships between ecosystem variables. Numerous studies (Raiesi and Beheshti, 2022; Martín-Sanz et al., 2022; Gao et al., 2024; Gao et al., 2025) have shown that NA provides more accurate results in identifying key indicators that influence soil health and their interrelationships. Thanks to its ability to visualise and quantify these interactions, NA has become an indispensable tool in ecological research, facilitating the development of more effective soil protection strategies. To gain deeper insights into the dynamics of soil health, we adopted a novel approach using NA to investigate the complex relationships between 14 soil health indicators within the total data set. This approach allowed us to identify complex, bidirectional relationships that provide valuable insights into the underlying processes and the strength of the links between these indicators. The NA framework consists of nodes (representing indicators) connected by edges representing positive or negative relationships between indicators. To account for the uneven distribution of soil health indicator values, a network model was created using the extended Bayesian information criterion (EBIC) in combination with the graphical least absolute clustering and selection operator (gLASSO) and a non-paranormal transformation. The EBIC hyperparameter (i), which was set to 0.50 (in the range from 0 to 0.50), controls the sparsity of the model and determines the number of edges included in the final network representation. Node centrality was used to assess the importance of each indicator within the network structure. Specifically, the strength centrality (SC) of each node was calculated, which quantifies its connectivity to other indicators in the network. Nodes with higher values for strength were identified as more central and influential within the network of soil health indicators. By analysing the network structure and identifying central nodes, NA provided important insights into the relationships and dependencies between soil health indicators.

This information was then used in further modelling to identify key indicators and determine weighting coefficients. The formula for calculating the strength of a node (i) is as follows:

$$SC(i) = \sum w(ij) \tag{1}$$

Where: $SC(i)$ is the strength centrality of node i; $w(ij)$ is the weight of the edge between nodes i and j; The summation is over all nodes j connected to node i.

2.2.4. Soil health evaluation methods

In this study, a comprehensive assessment of soil health was carried out by analysing fourteen key soil indicators: pH, OM, P, K, $CaCO_3$, clay content and PTEs including As, Cd, Cr, Cu, Hg, Ni, Pb and Zn. These indicators were selected due to their crucial role in soil productivity, soil degradation and overall soil security. It is important to emphasise that the aim of this study was not to minimise the data set (minimum data set, MDS), but to capture all relevant soil indicators at the regional level by using an extended data set (total data set, TDS). This approach allows for more accurate, consistent and reliable assessments as it includes a broader range of information that better reflects the complexity and diversity of soil characteristics. To ensure comparability and facilitate analysis, each soil characteristic was standardised using the Standard Scoring Function (SSF), with values transformed and normalised to a scale of 0.1 to 1.0. Three different SSF equations were applied: *"more is better" – N(x)*", *"less is better – M(x)"* and *"midpoint optimum (F(x)"*. The *N(x)* function was used for soil indicators where higher values are generally favourable, such as OM and available P and K (Karaca et al., 2020). Conversely, the *M(x)* function was applied to PTEs where lower concentrations are more desirable (Bayrakli et al., 2023). Specifically, the *M(x)* function was modified to account for stringent background thresholds for PTEs. This adjustment ensured that the *"less is better"* function peaks at concentrations corresponding to the calculated background values for the study area. The following background thresholds were used: As 17.78 mg kg^{-1}, Cd 0.55 mg kg^{-1}, Cr 58.19 mg kg^{-1}, Cu 30.88 mg kg^{-1}, Ni 46.68 mg kg^{-1}, Pb 26.91 mg kg^{-1}, Zn 89.88 mg kg^{-1} and Hg 0.17 mg kg^{-1} (MEP, 2018). The *F(x)* function was appropriate for attributes such as pH, clay content and others that have optimal ranges, with values outside this range being less favourable.

$$N(x)\left\{\begin{array}{cc} 1 & X \\ 1-0.9\dfrac{X-L}{U-L} & L \leq U \leq U \\ 0.1 & U \end{array}\right. \tag{2}$$

$$M(x)\left\{\begin{array}{cc} 0.1 & X < LX < L \\ 1+0.9\dfrac{X-L}{U-L}+0.1 & L \leq X \leq U \\ 1 & X > U \end{array}\right. \tag{3}$$

$$F(x)\left\{\begin{array}{ll} 0.1 & X < L \\ 0.9\dfrac{X-L}{U-L}+0.1 & L < X < U \\ 1 & U < X < U \\ 1-0.9\dfrac{X-L}{U-L} & L < X < U \\ 0.1 & X > U \end{array}\right. \tag{4}$$

Where X is the measured value for a soil property; L is lower limit threshold; U is upper limit threshold; and *N(x)*, *M(x)*, and *F(x)* are the SSF for high, low, and optimal limit threshold, which vary from 0.1 to 1, respectively.

$$SHI = \sum_{i=1}^{n} W_i(NA) \times N_{(x)}; M_{(x)}; F_{(x)} \tag{5}$$

Where *Wi(NA)* was the weight of the indicator resulting from the network analysis, *N (x)*; *M (x)* and *F (x)* was the score of each indicator in TDS, and n was the number of the selected indicators in TDS.

In order to define different levels, the SHI range was divided into five desired intervals. This resulted in a fixed interval width, which was successively added to the lowest SHI value to determine the upper limits of each interval (Sánchez-Navarro et al., 2015). This process resulted in the following quality classifications: Very low: SHI $\leq$ 0.327; Low: 0.327 $<$ SHI $\leq$ 0.436; Medium: 0.436 $<$ SHI $\leq$ 0.545; High: 0.545 $<$ SHI $\leq$ 0.654; Very High: SHI $>$ 0.654.

2.2.5. Noise sensitivity test

To evaluate the numerical robustness of the SHI, a noise sensitivity analysis was performed. Specifically, ±5% Gaussian noise was applied to all input indicators, and SHI values were recalculated using fixed weights obtained from NA. The comparison between the original and the perturbed SHI values was used to assess the sensitivity of the model to minor input fluctuations. The coefficient of determination (R^2), the mean absolute error (MAE) and the root mean square error (RMSE) between the original and the perturbed SHI values were calculated to quantitatively assess the stability. This procedure made it possible to check the stability of the model and reduced concerns about possible overfitting or random effects.

2.2.6. Self-organizing maps analysis

To gain a deeper understanding of the individual soil health indices and their interrelationships, we used a self-organising map (SOM), an unsupervised neural network. SOM arranges multidimensional data vectors on a typically two-dimensional grid of neurons, preserving the topological structure of the input data through a neighbourhood function. To ensure consistency and comparability, the data grid is normalised before SOM is applied.

In this study, SOM was applied at the raster scale, which allowed a detailed analysis of the spatial patterns within the data. Subsequently, the k-means algorithm was used to classify the indices into optimal clusters, which were determined by minimising the Davies-Bouldin index (DBI). This clustering procedure facilitated the identification of different groups of indices with similar characteristics.

A component-level diagram was created to visualise the relationships between the variables. This graphical representation provided important insights into the relationships and dependencies between the different soil health indices, improved the interpretation of the SOM results and helped to identify the most important grouping factors. In this analysis, 14 individual soil health indices were assessed using SOM to generate a self-organising neuron structure. The number of neurons was determined using a heuristic equation:

$$m = 5 \times \sqrt{n} \tag{6}$$

Where m means the amount of SOM map nodes, and n is the number of input data.

2.2.7. *Spatial heterogeneity analysis*

Our study investigates the spatial-causal relationship between independent variables (driving factors) and the dependent variable, the Soil Health Index (SHI). Specifically, we assume that the spatial clustering and distribution of factors influencing soil health mirror the spatial patterns and variations in soil properties resulting from these factors. The versatile GDM platform provides modules for factor detection, ecological exploration, risk detection and interactive exploration. Unlike traditional statistical methods, GDM can identify non-linear relationships among multiple influencing factors while accounting for spatial heterogeneity and stratification (Wang and Xu, 2017). Additionally, it can analyze interactive effects between pairs of independent variables and between independent and dependent variables.

For our analysis, we utilized a comprehensive set of nine independent variables (ST, SP, SE, LU, LF, EL, SL, HF, and DI) to evaluate their influence on SHI. Among these, three variables (LU, HF, and DI) are directly associated with human activities, reflecting the anthropogenic impact on soil health. The remaining variables represent natural factors, including EL, SE, ST, and others. This diverse selection provides a holistic perspective on the complex factors driving SHI variability. To ensure consistency and avoid classification inconsistencies, we applied the natural break method (Jenks, 1967) to classify the independent variables systematically (Lyu et al., 2024). For factor detection, the GDM computes Q value as follows:

$$Q_{value} = 1 - \frac{\sum_{h=1}^{L} N_{h^{\sigma^2}h}}{N^{\sigma^2}} \tag{7}$$

In the above formula, *L* stands for the number of different categories for a specific spatial factor. For discrete variables, L is directly equal to the number of distinct values. *Nh* and *N* denote the number of units within the *h-th* category and the total area respectively. The symbols $\sigma^2 h$ and σ^2 stand for the variance of the dependent variable within the *h-th* category or the total area. The *Q value* ranges from 0 to 1, with higher values indicating a stronger explanatory power of the spatial factor for the dependent variable.

The interaction detector identifies interactions between two explanatory variables *Q value* ($Xa \cap Xb$). It assesses whether the combined effect of these two factors *Xa* and *Xb* strengthens or weakens their influence on the dependent variable Y or whether their effects on *Y* are independent of each other. In the geographical detector, the interaction relationship between two factors is mainly divided into the following five categories: non-linear weakening, single-factor nonlinear attenuation, two-factor interaction enhancement, non-linear enhancement and mutual independence.

2.2.8. *Soil health disturbance assessment*

Soil health disturbances are deviations from optimal soil conditions that impair its ability to function as a resilient and active ecosystem. These disturbances can be of both anthropogenic and natural sources. Understanding the causes and consequences of these disturbances is critical to developing effective strategies to protect and restore soil resources.

To address this challenge, a comprehensive Soil Health Disturbance Index (SHDI) has been developed. The SHDI integrates the spatial values of different driving factors (*ANfI*) with their corresponding weights (*Wi*) to assess their combined impact on soil health. The weights were determined using the GDM method, where the q-values were standardised to represent the relative importance of each factor. Following the approach proposed by Lin et al. (2024), the SHDI was calculated using the following equation:

$$SHDI = \sum_{i=1}^{n} ANf_I \times QvalueW_I \tag{8}$$

Where *SHDI* is comprehensive anthropogenic and natural disturbance index, Anf_i is spatial value of anthropogenic and natural disturbances factors *i*, $QvalueW_i$ is weight of driving factor *i* and *n* is total number of driving factors. Once the SHDI values were calculated for each grid cell, they were categorised into three categories (high, medium and low) using the natural break classification method (Jenks, 1967). By classifying the SHDI values, the spatial patterns of disturbance across the study area were visualised. This classification enabled the identification of regions with different levels of anthropogenic and natural impacts on soil health, providing a clear basis for targeted management and mitigation strategies.

3. Results and discussion

3.1. *Descriptive statistics of soil indicators*

The descriptive statistics of the measured soil properties are shown in Table 1. The mean concentrations of As, Cd, Cr, Cu, Hg, Ni, Pb and Zn in the soil samples were 12.16, 0.82, 27.79, 29.64, 0.11, 24.5, 28.44 and 45.41 mg kg^{-1}, respectively. The coefficient of variation (CoefVar), which quantifies the variability and dispersion of pollutants of concern, revealed high values (over 100 %) for As, Cu, Hg and Pb, suggesting significant anthropogenic influences or other factors affecting their distribution (Dong et al., 2019; Su et al., 2023). Soil pH ranged from 2.5 to 7.6, indicating generally acidic conditions that could increase the availability of PTEs. Clay content ranged from 14 % to 39 %, with a mean of 24.3 %. The availability of phosphorus was low at most sites, while the availability of potassium was relatively high. The OM content ranged from 0 % to 14 %, with an average of 4.1 %. The standard deviation (StDev) was used to assess the dispersion of the data around the mean. The StDev of soil indicators increased in the following order: Hg (0.16) < Cd (0.75) < pH (1.12) < OM (1.77) < clay (3.32) < $CaCO_3$ (4.64) < potassium (10.78) < phosphorus (13.94) < chromium (23.86) < nickel (27.4) < lead (30.69) < zinc (37.86) < Cu (49.88) < As (55.03). The values for skewness ranged from 0.17 to 31.67 and for kurtosis from 1.13 to 1082.47, both of which indicate significant deviations from a normal distribution. High skewness values indicate a pronounced asymmetry, with a likely longer tail on one side of the distribution. Extreme kurtosis values signal the presence of strong outliers or extreme data points. These deviations from the normal distribution, especially for Cr, Ni, Zn, Pb, Cu and As (skewness and kurtosis values greater than 1), indicate possible anthropogenic influences or other factors that disturb the natural distribution of these elements (Proshad et al., 2024).

3.2. *Network structure and centrality measure*

In this study, network analysis served as a sophisticated tool to visualise and quantify the complex relationships between different soil properties. In particular, the network structure of the nodes of the soil indicators, the strength of the connections and the weighted adjacency matrix are shown in Fig. 3a and Fig. 3b and provide a diverse representation of the complex relationships between the analysed soil indicators. The thickness of the line between the nodes (indicators) indicates the strength of their relationships. The graph in Fig. 3a shows positive edges with solid lines and negative edges with dotted lines,

Table 1
Descriptive statistics of soil indicators of the study area.

Indicator	Mean	StDev	CoefVar	Minimum	Maximum	Skewness	Kurtosis
pH	5.252	1.12	21.33	2.5	7.6	0.17	1.13
OM	4.089	1.768	43.23	0	14.026	1.09	2.02
P2O5	10.35	13.935	134.63	0	104.09	2.61	8.26
K20	24.607	10.776	43.79	0	107.49	0.47	1.24
CaCO3	1.171	4.638	396.18	0	53.41	6.28	48.37
As	12.16	55.03	452.41	0	1965	31.67	1082.47
Cd	0.818	0.75	91.67	0	13.478	3.86	46.99
Cr	27.786	23.863	85.88	0.15	456.93	5.41	63.02
Cu	29.64	49.88	168.26	0.1	1285.83	12.71	246.26
Hg	0.105	0.156	148.95	0	1.666	5.29	33.97
Ni	24.5	27.396	111.82	0.058	580.36	7.25	106.26
Pb	28.439	30.687	107.9	0.1	707	8.83	136.07
Zn	45.411	37.862	83.38	0.1	740	7.82	106.99
Clay	24.298	3.32	13.66	14	39	0.45	1.23

which means that changes in one indicator are likely to influence changes in another. In general, the network analysis revealed significant edges (connections) within the network between pH, $CaCO_3$, K, P, OM and clay (Fig. 3a). In particular, pH shares many positive edges with $CaCO_3$ (weighting matrix 0.34), K with OM and P (weighting matrix 0.30), and clay with pH (weighting matrix 0.23) (Fig. 3b). These interdependencies confirm the crucial role of these indicators in determining soil fertility and overall soil quality. The exceptionally high connectivity within the network between Cr and Ni (weighting matrix 0.52) strongly suggests their common geological origin (Fig. 3b). A similar observation was made for Pb and Zn (weighting matrix 0.36), although their association is most likely due to anthropogenic influences. The high positive correlation in the network (weighting matrix 0.43) between As and Cd suggests that these indicators often act synergistically in the environment, with similar adsorption and desorption mechanisms at the soil surface leading to their joint mobility and thus increasing the risk of contamination of the ecosystem. In contrast to the other indicators analysed, Hg and Cu show significantly weaker associations with the other soil health indicators (Fig. 3a; b). This dissociation can be attributed to different sources of pollution and specific migration and transformation processes within the soil. For example, Hg can be present in various organic and inorganic forms, some of which are less mobile in the soil, while Cu can be bound to certain minerals or organic complexes, which limits its mobility.

Analysing the strength centrality (SC) provides valuable insights into the role of the different soil indicators within the network. As shown in Fig. 3c, pH, Cd and K proved to be the key indicators with the highest SC values (SC relative range 0.78——1), indicating their significant influence on the overall connectivity and stability of the network. The SC values of the soil indicators decreased in the following order: pH > Cd > K > Zn > Cr > Ni > Pb > P > $CaCO_3$ > OM > As > Clay > Cu > Hg (Fig. 3c). Soil pH is a fundamental factor in soil health and ecological balance and exerts a profound influence on various biological, chemical and physical soil processes (Yemefack et al., 2006). It plays a central role in regulating nutrient availability, microbial activity and soil structure and has a direct impact on plant productivity and ecosystem functionality. The optimum pH range for most soil processes is between 6.0 and 7.0, where nutrient solubility and microbial efficiency are maximised. Deviations from this ideal range can disrupt nutrient cycling, impair soil structure and inhibit plant growth, ultimately affecting agricultural productivity and environmental sustainability. Cd is classified as one of the 20 most hazardous substances in agroecosystems (Rai et al., 2019). Unlike many other pollutants, cadmium does not degrade naturally; instead, it accumulates and is transferred through the food chain, posing a serious threat to human health and the environment (Guo et al., 2022; Rezapour et al., 2024). Its geochemical behaviour in soil is influenced by numerous environmental factors, including pH, soil texture, organic matter content, redox conditions and the presence of other ions (Duan et al., 2024). K is an essential mineral element for plants, playing a crucial role in their growth and development. It is involved in numerous physiological processes, including nutrient uptake, photosynthesis and protein synthesis. Adequate K levels are essential for maintaining plant health and maximising crop yields. Conversely, indicators with lower SC values, such as Hg (SC = 0.22), Cu (SC = 0.29) and P (SC = 0.30), showed a weaker influence within the network. Although these indicators still contribute to the overall function of the network, their influence on its connectivity and stability is probably less significant.

The SHI integrated by weights (SC) from the TDS determined by NA with the respective indicator was (Fig. 3d):

$$SHI = 0.125_{pH} + 0.061_{SOM} + 0.062_{P} + 0.106_{K} + 0.062_{CaCO3} + 0.061_{As} + 0.110_{Cd} + 0.073_{Cr} + 0.041_{Cu} + 0.032_{Hg} + 0.067_{Ni} + 0.067_{Pb} + 0.075_{Zn} + 0.058_{Clay}$$

3.3. Classification and distribution of SHIs via SOM

To explore the spatial variability and relationships among soil health indicators, a 15 × 15 hexagonal SOM map was constructed (Fig. 4a). The U-matrix, a distance-based representation of the SOM map, revealed clear patterns in the distribution of individual indicators (Fig. 4b). Subsequently, using the K-Means clustering algorithm, the samples were classified into five clusters based on their similarity with respect to soil health indices (Fig. 4c). When interpreting the results, it is important to pay attention to the index values (Fig. 3), which lie between 0.1 and 1.0 and result from the functions $N(x)$, $M(x)$ and $F(x)$ (Eqs. (2)–(4)). Lower index values indicate less favourable properties from the point of view of soil health, while higher values indicate more favourable properties of the indices analysed.

Cluster I is primarily characterised by the individual indices of Pb, Ni, Cu, Cr and Zn. The distribution patterns of the indices show relatively large similarities, with higher index values generally concentrated in the central and southern parts of the hexagons, while lower values dominate in the western and eastern parts (Fig. 4). For example, lower Ni_{index} and Cr_{index} values are associated with serpentinised geological formations in the southwestern part of the study area, especially along the eastern slopes of Mount Kopaonik (Stevanović et al., 2018), as well as in the northeastern areas around Mount Deli Jovan (Mrvić et al., 2010). A similar pattern is observed in the central and northern parts, especially around the courses of the Great and Western Morava rivers (Mrvić et al., 2011; Mrvić et al., 2013; Čakmak et al., 2023). Previous research in central-eastern Serbia has shown that fluvisols formed by material deposition during the Holocene are characterised by higher concentrations of Ni together with elevated levels of Cr and Pb (Jakovljević et al., 1997). These data suggest that the content of these elements in fluvisols is inversely proportional to the age of the soil. The south-eastern part of the hexagon with lower Pb and Zn_{index} values can be associated with the dacites and andesites of Kopaonik Mountain (Čakmak et al., 2023). On the other hand, the northern and western

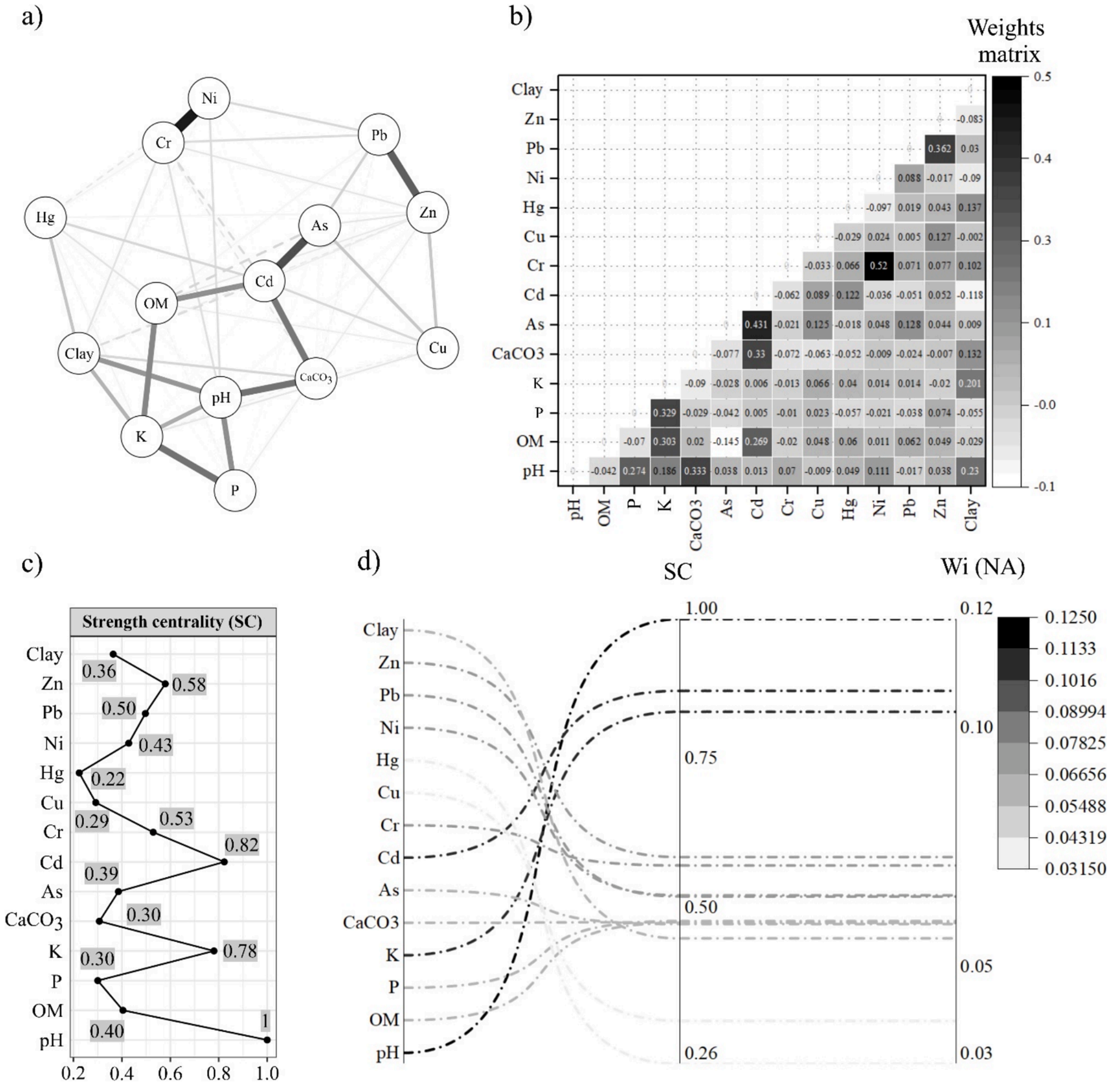

Fig. 3. (a) network structure of the soil indicators nodes, (b) network weight matrices (c) centrality (strength) plot (d) contribution weight of soil indicators.

parts of the hexagon with the above-mentioned indices are associated with emissions from traffic (leaded petrol, brake wear and catalytic combustion) and tyre wear (Zhang et al., 2020; Dragović et al., 2023), especially near busy roads and important transport hubs such as Belgrade and Niš (Pavlović et al., 2021). It is also important to note that industrial activities and agricultural practises can introduce Pb and Zn into the soil through the use of fertilisers, manure and pesticides (Guo et al., 2022). Lower Cu_{index} values are characteristic of the north-eastern part of the hexagon (Fig. 4) and are influenced by the ore deposits around Bor and Majdanpek (Mrvić et al., 2010; Mrvić et al., 2013) as well as the copper-rich andesite and dacite massifs (Pavlović et al., 2017). In contrast, the eastern areas are primarily affected by agricultural production, particularly the use of pesticides, especially in fruit growing and viticulture (Mrvić et al., 2009). In vineyards in eastern Serbia, for example, copper-based fungicides are used on a large scale to combat downy mildew on grapevines (Ninkov et al., 2014). According to Kadović et al. (2005), the analysis of PTEs concentrations in the organic soil layers of the main forest ecosystems in Serbia provides clear evidence that atmospheric deposition is the main source of these elements in forest soils, which further emphasises the role of anthropogenic factors in disrupting natural cycles and forest health. These adverse effects are particularly pronounced in coniferous forests, which, according to Kadović and Knežević (2003), act as significant accumulators of PTEs. Their comprehensive study also shows that deciduous forests can also accumulate significant amounts of these pollutants under certain conditions, which further increases the risk to forest ecosystems.

Cluster II is characterised by the following indices: pH, OM, nutrient availability (P and K) and clay. The spatial distribution of the pH_{index} is closely related to the geological substrate. Higher values of the pH_{index} are influenced by carbonate rocks in the central part of the hexagon and

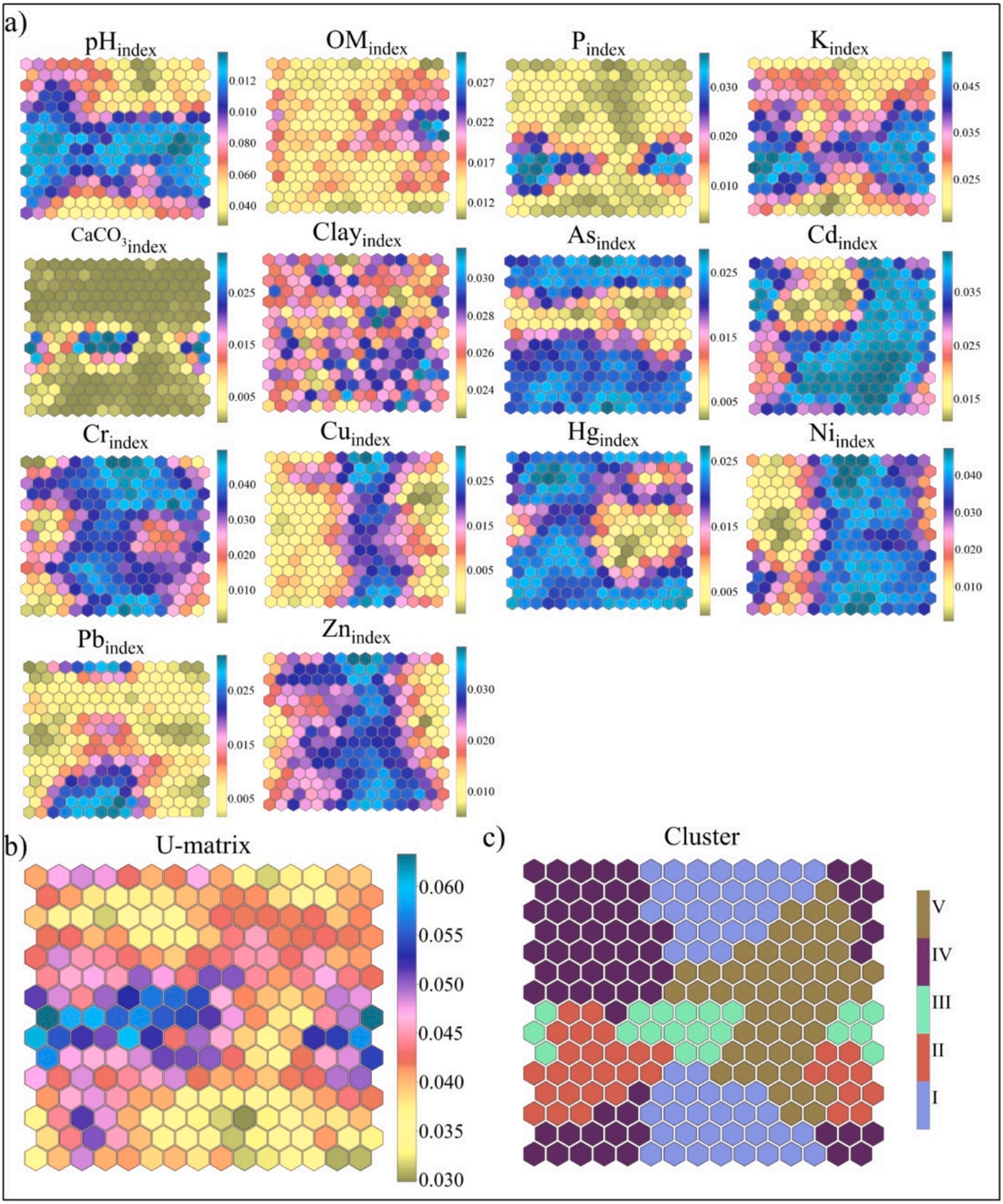

Fig. 4. SOM matrix map of the components: (a) individual soil health indices, (b) U-matrix and (c) cluster map.

serpentinite rocks in the western part of the hexagon (Čakmak et al., 2023). On the other hand, lower pH_{index} values are widespread both at lower elevations, where stagnosols dominate, and at higher elevations, where district Cambisols and Leptosols are present. A particularly pronounced acidity is observed in the vicinity of the Bor mining area, where anthropogenic influences, especially sulphur dioxide emissions from mining, further deteriorate soil health. Vertisols, Cambisols formed on andesite and sandstone, and Fluvisols contaminated with mining waste were found in this area (Mrvić et al., 2009). Analyses of the indices for the availability of phosphorus (P_{index}) and potassium (K_{index}) show similar spatial patterns to the pH_{index}. Higher values of these indices were found in the western and eastern parts of the hexagon, indicating a potentially higher availability of phosphorus and potassium in these areas, while lower values of the mentioned indices occur in the northern and southern parts of the hexagon, especially in acidic soils where phosphates combine with soluble Al and Fe and are less available to plants. Many studies indicate a direct dependence between pH and the content of available phosphorus in the soil, while the potassium content in the soil can be influenced by the chemistry of the parent material, land use and climatic conditions (Ballabio et al., 2019). However, it should be noted that nutrient availability is also influenced by other factors, such as organic matter content. Soil organic matter content (OM_{index}), which is particularly high in the forest ecosystems in the eastern part of the study area, plays a crucial role in maintaining soil structure, water retention and creating favourable conditions for the development of microorganisms that contribute to soil mineralisation processes (Perović et al., 2023). In addition, OM has a significant effect on the solubility and toxicity of PTEs such as Pb, As and Cu, thus indirectly influencing their distribution and behaviour in the soil (Fan and Liang, 2025). Clay soils ($Clay_{index}$), which are mainly distributed in the central and western parts of the hexagon, are known for their high fertility due to their increased cation adsorption capacity, which enables them to efficiently store and utilise larger amounts of nutrients such as potassium, calcium and magnesium. In addition, clay content has a significant effect on soil erodibility, with soils with a higher clay content being more resistant to erosion (Perović et al., 2023) and further preserving their structure and fertility.

Cluster III was mainly associated with the $CaCO3_{index}$. The relationship between CaCO3 and soil health is complex and multi-layered. For example, low values of the $CaCO3_{index}$, especially in the central part of the hexagon and in combination with a low pH_{index}, can reduce the solubility and availability of important nutrients such as iron, zinc and manganese. This can lead to nutrient deficiencies in plants and affect their growth and development (Serda Kaya and Dengiz, 2024).

Cluster IV was associated with elevated values of the arsenic (As) and mercury (Hg) indices. Low values of the As_{index} in the central part of the hexagon are closely related to agricultural activities in this area as well as to industrial sources around the Bor mining area (Mrvić et al., 2013) and to wastewater and gas emissions, as some previous studies show (Jiang et al., 2020; Guo et al., 2022). It is estimated that the production processes in the boron mine lead to the annual release of 300–500 tonnes of sulphuric acid, 300–500 tonnes of arsenic, 30–100 tonnes of lead and 10–35 tonnes of zinc (Pavlović et al., 2017). In addition, fertilisers and pesticides can contribute to arsenic pollution in river systems, while coal combustion is an important source of mercury, which later accumulates in the soil through atmospheric deposition (Cai et al., 2024). However, the spatial distribution of arsenic and mercury in soils can be influenced by geological composition (Qiao et al., 2022), with sedimentary rocks generally having a higher arsenic content than volcanic rocks.

Cluster V is characterised by a high Cd_{index}, which is mainly concentrated in the western, southern and north-central regions. The low Cd_{index} values in the north-eastern part of the hexagon clearly indicate an association with agricultural practises, including the use of phosphate fertilisers, organic fertilisers and certain pesticides and herbicides (Pavlović et al., 2017). It should be emphasised that the adsorption of Cd increases with pH, while the presence of $CaCO_3$ in the soil significantly reduces its mobility and availability to plants and microorganisms. In addition, wear and tear of tyres and traffic can provide evidence of the anthropogenic origin of Cd in soil (Čakmak et al., 2018).

3.4. Spatial distribution and robustness of the SHI

The spatial distribution of soil health in eastern Serbia shows considerable spatial differences that reflect the complex relationships between the different soil health indicators (Fig. 5c). According to the analysis, 51.4 % of the area belongs to the high SHI category. These areas are mainly located in the central parts of the study area and are characterised by exceptionally favourable physical and chemical properties. The soils in this category have an optimum pH value, a high OM content and sufficient concentrations of nutrients important for plant growth, such as phosphorus and potassium. At the same time, the concentrations of PTEs such as lead, cadmium and mercury are within the permitted limits, which further confirms the healthiness of these soils. The next significant group is 44.4 % of the land area, which is categorised as moderately healthy. These areas represent complex combinations of positive and negative influences of different soil health indicators. For example, while soils in these areas often have acceptable nutrient concentrations, they may also be deficient in OM or have elevated levels of certain PTEs. Despite some limitations in terms of soil health, these areas still have potential for soil health improvement. Smaller, fragmented areas with very high SHI, representing 2.1 % of the total area (Fig. 5c), are mostly located in preserved forest ecosystems or in areas with exceptionally stable soil health indicator values. These soils are exposed to minimal human impact, which helps to maintain the natural balance. On the other hand, low and very low SHI values, representing 2 % and 0.1 % of the total area, represent regions with serious ecological problems. These zones are mainly located in the north, south and south-west of the region, often close to mining and industrial centres. Intensive anthropogenic impacts, including the exploitation of natural resources, uncontrolled waste disposal and pollutant emissions, have contributed to the accumulation of PTEs. This pollution not only has a negative impact on soil health, but also poses a potential threat to human and animal health.

In addition, the numerical robustness of the SHI was systematically assessed through a noise sensitivity analysis in which ± 5 % Gaussian noise was independently applied to all input indicators, while the weighting scheme remained constant. Based on the perturbed indicators, new SHI values were recalculated and subsequently compared with the original index scores to evaluate the stability of the composite indicator under minor input fluctuations. As shown in Fig. S2, the results demonstrated a very strong linear relationship between the two sets of SHI values ($R^2 = 0.910$), with minimal deviations reflected in a mean absolute error (MAE) of 0.014 and a root mean square error (RMSE) of 0.018. These results provide strong empirical evidence that the SHI is numerically stable, can withstand small stochastic perturbations and is unlikely to produce biassed results due to small variations in the underlying input data.

3.5. Relative effects of individual driving factors

It is known that the spatial distribution of soil health results from the interaction of numerous factors whose effects are not isolated, but often act synergistically or antagonistically (Xu et al., 2023; Pan et al., 2024). As Bünemann et al. (2018) emphasise, external factors such as parent material, climate, topography and hydrology have a decisive influence on soil health. Our study further confirms these results and emphasises the importance of extrinsic factors for the spatial distribution of soil health in eastern Serbia, where ST and SP were identified as key factors (*Q values of 0.26 and 0.24*). The formation of soils on different parent materials leads to different mineral and organic compositions, with natural factors having the strongest influence on soil health and fertility

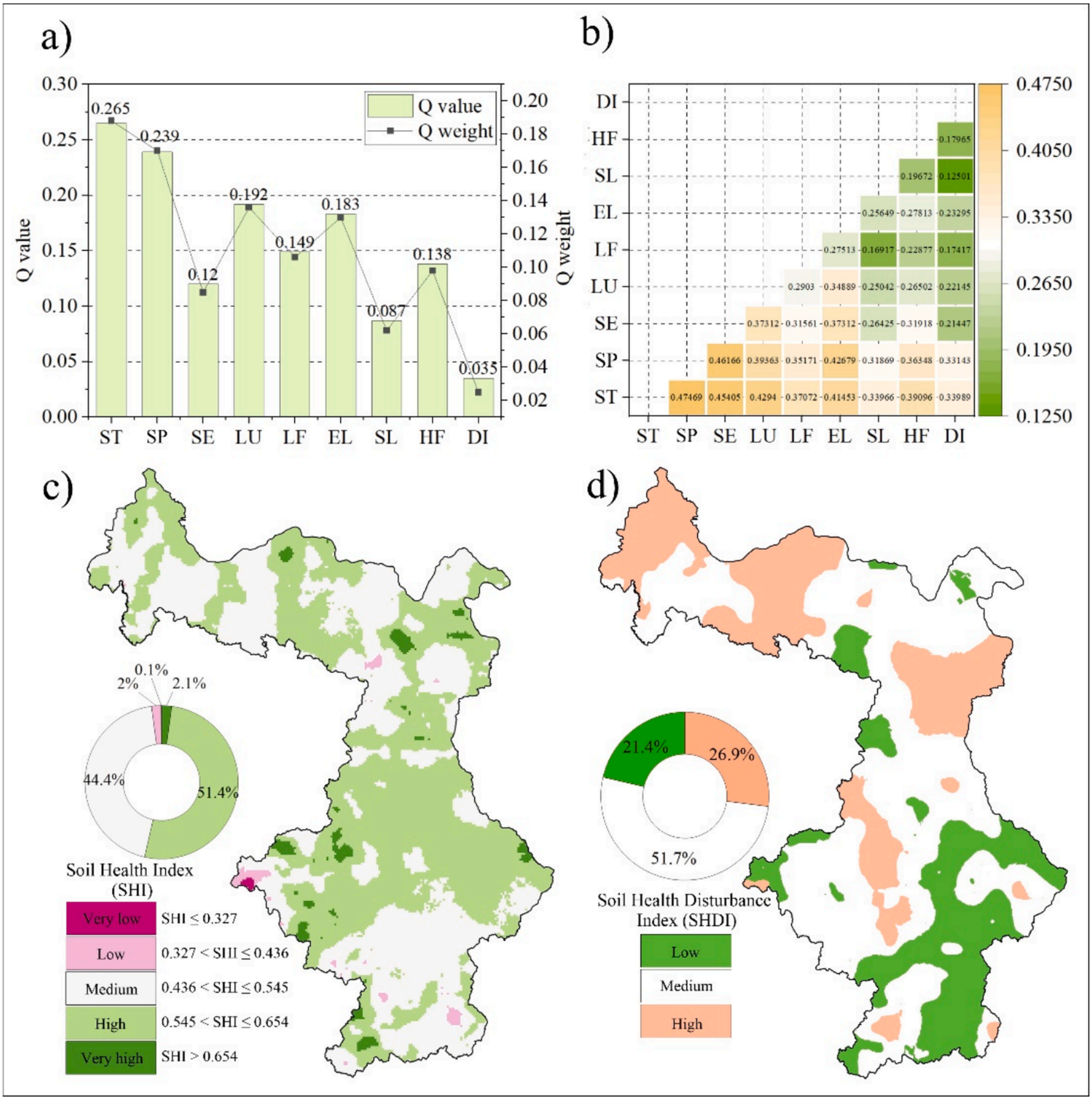

Fig. 5. Evaluation of soil health in eastern Serbia: (a) indicator weights revealed by the factor detector; (b) influence matrix diagram based on interaction detector analysis; (c) spatial distribution of soil health grades (d) spatial distribution of comprehensive soil disturbance.

in regions with low industrial activity (Wang et al., 2020). In eastern Serbia, eutric and district cambisols and leptosols predominate (Pavlović et al., 2017), whose properties and fertility largely depend on the parent material (Wilson, 2019). Eutric cambisols, which are most common in the relatively shallow areas of the Belgrade and Danube districts, form on loess, alluvium and lacustrine sediments. They are characterised by a great depth, a sandy-clay texture and a high nutrient content (Pavlović et al., 2017). These characteristics make them ideal for agricultural production, where soil health is further improved through increased biological activity and efficient retention of plant nutrients. In contrast, district cambisols, which occur mainly in the north-eastern parts (Braničevo and Bor), are associated with acidic silicate rocks such as shale, sandstone and granite. The influence of these parent rocks leads to highly acidic soils, low OM content and reduced biological activity, which significantly affects the health of the soils and limits their productive value. The most important group of soils in eastern Serbia are leptosols, which are found mainly at higher altitudes, although their spatial distribution depends largely on the properties of the parent material. The south-eastern part of the region, for example, is characterised by schist of varying composition and gneiss, i.e. metamorphic rock that decomposes quickly and physically. On these substrates, poorly bonded soils with a powdery or fine-grained structure, sandy-clayey and clayey composition and high content of skeletal material are formed (Pavlović et al., 2017). Limestones, the most widespread carbonate rocks, especially in the Niš and Bor regions can have high concentrations of elements such as Cd, Pb and As. This phenomenon is the result of secondary enrichment processes that occur during the formation of new minerals. In these processes, metals are selectively bound to certain minerals, leading to their concentration in localised areas (Zha et al., 2024). In addition, the data suggest that ST and SP shape the physico-chemical properties of the soil, which directly affect the pH, adsorption and migration of PTEs, as shown in the studies by Zhang et al. (2022b) and Duan et al. (2024).

Topographical factors such as elevation (EL) play an important role in the distribution of SHI (Q value = 0.18). This result is in line with the findings of Bi et al. (2024) and Paul et al. (2020) as well as with previous studies conducted in Serbia (e.g. Perović et al., 2025). Elevation influences microclimatic conditions, precipitation and temperature fluctuations, which in turn affect the migration, accumulation and speciation of elements in the soil (Aqdam et al., 2023; Ma et al., 2023). At higher altitudes, such as in the Toplica, Jablanica and Pčinja regions, where temperatures are lower and precipitation is higher, chemical processes in the soil are slower, which can affect the mobility and storage of PTEs (Wang et al., 2024). Increased precipitation, which is considered an important factor in soil pH, can lead to soil acidification (Slessarev et al., 2016). Topographic features such as landform and slope (Q values = 0.15 and 0.09, respectively) contribute to the control of erosion processes and water flow by redistributing elements and enriching or depleting certain soil horizons, thereby altering the physical properties of the soil and affecting its erodibility (Aqdam et al., 2022).

The type of land use (LU), with a *Q value of 0.19*, plays a crucial role in maintaining and improving soil health, regardless of whether it is forest, meadow, arable land or urban areas. The forest ecosystems in eastern Serbia, which cover around 40 % of the entire territory, have a stabilising effect on soil health. The richness of organic matter and the continuous renewal of the vegetation cover contribute to the accumulation of nutrients and significantly reduce the risk of soil erosion. Similar results have been confirmed in numerous studies indicating that forest soils generally have better health compared to other soil types (Huang et al., 2021). These results emphasise the importance of forest ecosystems in maintaining soil health and their contribution to the sustainable management of natural resources.

Soil erosion (SE), with a recorded *Q value of 0.12*, is particularly pronounced in the Nišava district (Manojlović et al., 2017), where soil losses exceed 15 t ha^{-1} yr^{-1} (Perović et al., 2012), and has a significant negative impact on soil health. This process leads to the loss of topsoil, the most fertile layer, which is rich in organic matter, essential nutrients and microorganisms necessary for maintaining soil fertility and productivity. Erosion not only impoverishes the soil, but also destroys its structure, reduces its ability to store water and nutrients, and hinders regeneration in degraded areas. In addition to the direct impact on soil health, SE leads to the deposition of eroded material in watercourses and water accumulations, introducing large amounts of pollutants such as pesticides, fertilisers and PTEs that further endanger ecosystems (Perović et al., 2019). The results show that industrial activities such as mining, metallurgy and energy production have promoted the economic development of many countries, but their negative impact on the environment, especially on soil health, is undeniable (Chen et al., 2024). The industrial areas in Eastern Serbia are characterised by high PTEs emissions, especially in the energy, construction and chemical industries (SEPA, 2018). Although it was expected that industrial activities (DI) would have a significant impact on SHI, our results show that this factor is not significant (*Q value 0.035*). In contrast, the human footprint as a complex indicator encompassing different aspects of human activities showed a more significant influence on the spatial distribution of soil health (*Q value 0.14*). This result underlines that it is not only direct industrial activity that is decisive, but the entire cumulative influence of humans, including urbanisation, infrastructure and all aspects of human activity that together influence soil health.

3.6. Interactive influences of driving factors

The interactive effects of nine key factors were assessed using the GDM and are shown in Fig. 5b. Previous studies repeatedly emphasise the significant influence of the combination of anthropogenic and natural factors on soil health (Huang et al., 2021; Zha et al., 2024; Bai et al., 2024). In particular, natural factors such as soil type (ST) and parent material (SP) are the main factors influencing soil health in eastern Serbia. Their interaction ($ST \cap SP = 0.47$) has the strongest explanatory power compared to the contributions of the other interactions. Moreover, the interactions of ST and SP with all other factors exceed a value of 0.33, confirming these factors as key drivers of soil health heterogeneity (Fig. 5b). Although the anthropogenic factor, industrial development (DI), has a weak individual impact, its synergistic power increases significantly when combined with natural factors, especially ST, SP, SE and EL. For example, the combined effects of DI are stronger than its individual effects ($DI \cap ST = 0.34 > DI$; $DI \cap SP = 0.33 > DI$). This suggests that human activities, when acting in synergy with natural factors, can have a much greater impact on changes in soil health (Proshad et al., 2021).

We found that natural factors such as soil erosion (SE) and elevation (EL) amplify the effects of human activities. Thus, the interaction $SE \cap HF$ yielded a Q value of 0.32, while $EL \cap LU$ reached a value of 0.35, illustrating the significant influence of natural conditions on the amplification of anthropogenic impacts. Human activities often accelerate soil erosion, which has serious ecological, economic and social consequences (Manojlović et al., 2018). At the same time, elevation shapes climatic conditions, vegetation, soil structure and the availability of resources, which directly affect land use patterns. Similar trends were observed for other factors, suggesting that the full contribution of some factors only materialises through their interaction with other factors, with the interactions revealing pronounced, enhanced nonlinear effects. It was particularly emphasised that the interactions between the natural factors were stronger than those between the human influences. Furthermore, the combined effects of different natural factors were found to be more significant than the effects of purely anthropogenic factors. Even when individual factors had a relatively small influence, their interaction with other factors often led to increased non-linear effects. Similarly, the interaction of factors with large individual effects amplified the non-linear effects, confirming their key role in shaping soil health.

3.7. Identifying the spatial patterns of factors driving soil health disturbance

The extent of anthropogenic and natural influences on soil health in eastern Serbia was quantified using the Soil Health Disturbance Index (SHDI). The results show that 26.9 % of the territory is significantly affected by these factors, especially in the north-western part of the analysed area. For example, the Belgrade region as a centre of urbanisation, industrialisation and intensive agriculture shows the strongest impacts (Fig. 5d). The Belgrade region, with a GDP per capita of around USD 13,000, which is 62.6 % higher than the national average (SORS, 2023), indirectly contributes to increased emissions of harmful elements into the soil, including PTEs and nitrates, thus threatening soil health. In addition, there are three thermal power plants in the city of Belgrade ("Nikola Tesla-A"," "Nikola Tesla-B" and "Kolubara"), whose operation further degrades soil quality and negatively affects human health through direct and indirect processes (Pavlović et al., 2018). In addition to urban and agricultural activities, the mines in Bor and Majdanpek also contribute negatively to soil health in the north-western part of the study area.

As mentioned above, the extraction and processing of ores releases PTEs such as Cu, Pb, Cd, Hg and As (Serbula et al., 2017), which contaminate the soil and jeopardise local ecosystems. Mining activities further contribute to soil degradation, especially in the vicinity of landfills and open pits. In the northern part of the study area, in the Velika Morava river catchment (Podunavski district), high SHDI values were found, reflecting the complex interplay of anthropogenic and natural factors. A similar pattern was observed in the south-eastern part of the region, in the South Morava river catchment (Nišavski district), where different influences overlap and characterise the spatial diversity of soil health. A medium SHDI covers 51.7 % of eastern Serbia, while 21.4 % of the area is affected by a low SHDI. These areas, located mainly in the northern, central and southern parts of the region, are characterised by a decline in industrial and agricultural activities, depopulation and migration of the population to the northern parts of the country. The forest ecosystems that predominate in these areas contribute significantly to the preservation of natural soil characteristics. In particular, the south-eastern part of the analysed area, which includes the Pčinja district and especially the municipalities of Bosilegrad and Trgovište, is characterised by a low SHDI value. This region is characterised by minimal human activity, mainly due to its low population density and lack of significant industrial development. Moreover, it is the region with the highest rural poverty and unemployment in Serbia, as emphasised in the study by Bogdanov et al. (2008).

4. Advantages and limitations

This study makes several important contributions to the assessment of soil health. It applies an innovative methodological framework that aims to overcome the limitations in integrating and optimising soil health indicators by using a standardised and reproducible approach. In contrast to conventional methods, which often emphasise either statistical associations or empirical thresholds, the proposed framework identifies the main drivers of soil health, enables spatial visualisation of individual indicators and disentangles the respective roles of anthropogenic and natural influences.

In addition to presenting this framework, the study also critically examines the strengths and limitations of new analytical techniques. Network analysis has great potential to reveal complex interrelationships between soil variables and provide insights that are often not accessible using conventional statistical methods. However, its effectiveness is highly dependent on the quality, completeness and representativeness of the input data, as incomplete or biassed data sets can distort the network topology and misrepresent the importance of the variables. Self-Organising Maps further contribute by capturing nonlinear relationships and preserving topological patterns in soil health data, enabling the detection of gradients and latent structures that may be missed by linear methods. However, the SOM approach involves subjective decisions about key model parameters such as map dimensions, learning rates and neighbourhood functions, which can introduce bias and affect reproducibility. Furthermore, the GDM effectively quantifies the spatial explanatory power of environmental factors and their interactions, but it requires discretisation of continuous variables, which can lead to information loss if categorisation thresholds are not carefully defined.

In addition, several important challenges and future directions arise in the context of the broader concept of soil health. One major challenge is to summarise multiple soil properties into a single index value (Prince et al., 2018). While this approach is useful for summarising complex information, it carries the risk of information loss and may overlook specific soil constraints, especially if the selection of indicators is not well tailored to the regional soil-environment context. Furthermore, SHI models developed in one geographical setting may not be directly transferable to other regions due to differences in soil and climate conditions, emphasising the need for cross-regional calibration and validation (Aqdam et al., 2023).

To improve the robustness of SHI frameworks, future research should prioritise expanding the range of indicators included, especially those that capture biological aspects of soil function. Biological measures such as microbial biomass, enzyme activities and biodiversity indices are crucial for a holistic assessment of soil health. Improved data collection protocols that are harmonised in terms of sampling depth, replication, timing and methods are also essential (Stewart et al., 2018). The development of a universal soil health classification system would further improve cross-study comparability, policy relevance and scalability.

Beyond methodological refinement, future studies should examine both the spatial and temporal dynamics of soil health. The integration of long-term data sets is crucial for the production of context-sensitive and policy-relevant assessments. As Rinot et al. (2019) suggest, there is also an increasing need to broaden the soil health framework by explicitly including ecosystem services (ES) as outcome variables, rather than relying solely on soil condition indicators.

Finally, the integration of advanced technologies such as high-resolution sensors, cloud computing infrastructures and machine learning-based analytics has significant potential to transform soil health assessment. These innovations can enable real-time monitoring, improve spatial and temporal resolution and provide a more nuanced understanding of soil system dynamics (Fausak et al., 2024).

5. Conclusions

This study provides valuable insights into the complex processes and factors that determine soil health in eastern Serbia. It uses an innovative methodological framework, NA-SOM-GDM, which integrates Network Analysis (NA), Self-Organising Maps (SOM) and the Geodetector Model (GDM). A detailed analysis of over 2,500 soil samples from eastern Serbia revealed that key indicators such as pH, cadmium (Cd) content and potassium (K) concentration are crucial for assessing the condition and health of this natural resource. More than 51 % of the surveyed area was classified in the high Soil Health Index (SHI) category, with the central and partly north-eastern regions identified as with favourable physico-chemical properties. Natural factors, including geological substrate, soil type, elevation and land use, showed significant individual impacts on the spatial heterogeneity of soil health, as well as strong interactions that generated pronounced amplifying nonlinear effects. On the other hand, among the anthropogenic factors, the human footprint dataset stood out, reflecting the intensity of different human activities such as urbanisation, population density and agricultural practises that contribute to the spatial heterogeneity of soil health. The interactions between natural and anthropogenic factors indicated synergistic effects, with natural factors having a dominant influence, while the full contribution of anthropogenic factors only became apparent through their interaction with natural factors.

One of the important contributions of this research is the development of a quantitative Soil Health Disturbance Index (SHDI), which allows accurate mapping of the impact of both natural and anthropogenic factors at a regional scale. The SHDI was used to identify areas of high, medium and low soil disturbance, providing detailed insights into spatial variations and highlighting critical intervention points for soil protection. Furthermore, the SHDI developed in this study is adaptable and can potentially be customised for use in other studies worldwide.

Therefore, the results of this study pave the way for a significant improvement in soil resource protection strategies by integrating scientific knowledge and practical solutions for efficient and sustainable management, while recognising certain limitations and providing a basis for refinement and wider application of the proposed framework. Further research efforts should aim to harmonise and adapt soil health assessment methodologies to local and regional ecosystem specificities in order to support consistent approaches and informed decisions on soil protection.

CRediT authorship contribution statement

Veljko Perović: Writing – original draft, Visualization, Software, Methodology, Conceptualization. **Vesna Mrvić:** Supervision, Investigation, Conceptualization. **Dragan Čakmak:** Validation, Methodology, Formal analysis. **Biljana Sikirić:** Formal analysis. **Zoran Dinić:** Formal analysis, Data curation. **Miroslava Mitrović:** Writing – original draft, Formal analysis. **Pavle Pavlović:** Supervision, Methodology, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.compag.2025.110664.

Data availability

The authors do not have permission to share data.

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