

Review

Integrating systematic review and Bayesian weighting to derive a minimum dataset for soil health assessment in arid and semi-arid regions

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ABSTRACT

Soil health assessment in arid and semi-arid regions necessitates strong frameworks capable of combining a wide range of physical, chemical, and biological indicators. This study systematically analyzed 141 manuscripts to establish a Minimum Dataset of soil health indicators and to refine their relative importance through a Bayesian weighting approach. The selection methodology yielded a core collection of six physical, four chemical, and two biological indicators. Since each of the 141 studies considered reports its own subset of soil health indicators, not a common and homogeneous set shared by the entire literature, but a specific selection from time to time defined by individual authors, synthesizing data from heterogeneous sources generates a structural problem of missing data when attempting to estimate a unique and comparable weight vector across studies. To solve this problem without resorting to ad hoc imputation of the missing numerical values, a Bayesian Expectation-Maximization algorithm was developed, which iteratively redistributes the missing probability mass of the indicators not reported in each study, in proportion to the weights currently estimated for the entire corpus, until convergence to a final, probabilistically consistent weight vector. This approach allowed us to distinguish the weights obtained for the global dataset (arid and semi-arid regions) and for the Mediterranean basin. Globally, the most influential indicators were soil organic carbon, electrical conductivity, cation exchange capacity, bulk density, and pH, indicating a balanced contribution of physical and chemical parameters. In contrast, the Mediterranean dataset demonstrated a different pattern, with soil microbial respiration and soil organic carbon emerging as prominent markers, followed by clay content, silt, and cation exchange capacity playing minor roles. This Bayesian-weighted MDS offers a transferable, quantitatively grounded alternative to existing soil health assessment frameworks for arid and semi-arid regions.

1. Introduction

Soils represent the primary foundation for the Earth's biosphere, enabling it to sustain local, regional, and global environmental quality (Rinot et al., 2019) and security of food production (Kopittke et al., 2019; Lal, 2008); hence, the importance of soil health (SH) cannot be underestimated. SH, as defined by the Natural Resources Conservation Service (NRCS), is the capacity of soil to serve as an essential living ecosystem that sustains plants, animals, and humans (Moebius-Clune et al., 2016). SH can be assessed through several soil indicators, including chemical, physical, and biological features (de Paul Obade and

Lal, 2016). Soil chemical indicators illustrate the essential interface between the soil solid phase and the soil solution, regulating nutrient flux and ecosystem-level functionality (Smethurst, 2000). Beyond facilitating plant nutrition, these indicators are pivotal in environmental monitoring, as they govern the bioavailable fraction of soil contaminants and their risk of translocation within the agroecosystem (Cataldo and Wildung, 1978). Physical indicators portray the soil's capacity to support plant growth through their influence on the movement, retention, and availability of water and nutrients; the plant root penetration capacity; and the flow of heat and air within the soil (Sainju et al., 2022; Gardner et al., 1999). Additionally, biological indicators reflect the

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abundance, diversity, and activity of soil organisms, particularly microbial communities ranging from heterotrophs to autotrophs, and provide insight into soil fertility status and the functioning of biogeochemical cycles (Basu et al., 2021; Moebius-Clune et al., 2016). However, rather than relying on individual indicators, their integrative approach allows SH to be assessed across diverse soil types and ecosystems, which is essential for identifying areas of constraints and supporting sustainable soil management strategies for crop production (Nabiollahi et al., 2017, 2020; Biswas et al., 2017; Andrews et al., 2004). Therefore, quantifying SH has become mandatory for decision-making and for improving our understanding of soil ecosystems to accelerate agricultural productivity (Sathiyamurthi et al., 2024). This is further reflected in recent European policy initiatives, such as the EU Soil Monitoring Law, which formally embeds soil health assessment into a harmonized regulatory framework to support evidence-based management and long-term soil resilience (European Commission, 2025). Many soil health assessment (SHA) indices have been developed throughout the years (Bünemann et al., 2018; de Paul Obade and Lal, 2016; Andrews et al., 2004), and their usage encouraged comparison among similar soils and enabled the assessment of a particular field's position on an SH continuum (Stott, 2019; Armenise et al., 2013). Although there is no golden standard set of criteria for assessing SH, similar studies typically used a dataset with a comparable structure and common indicators (Kazemi et al., 2016; Akinci et al., 2013). Usually, SHA tools estimate a soil quality index (SQI) from a set of soil health indicators (SHIs) that can encompass the total number of chosen parameters or can be reduced to a minimum dataset (MDS). The resulting SQI is generally presented in an easy and flexible format based on an integrated evaluation of the indicators and their weights (Santos-Francés et al., 2019; Turan et al., 2019). An appropriate MDS streamlines SQI assessment by reducing measurement time and costs, while eliminating collinearity and data redundancy (Samaei et al., 2022; Sheidai Karkaj et al., 2019; Raiesi, 2017). Numerous studies have demonstrated that an MDS can represent soil quality nearly as effectively as the total dataset (Wang et al., 2023; Li et al., 2019; Emami et al., 2024). MDS selection may be achieved through expert judgement based on ecological relevance, management goals, and available constraints (Doran and Parkin, 1994). However, MDS selection in contemporary research is predominantly guided by statistical data-reduction methods such as principal component analysis (PCA), redundancy analysis (RDA), factor analysis (FA), and discriminant analysis (Gan et al., 2024; Hu et al., 2021; Mei et al., 2019; Gong et al., 2015; Liu et al., 2014).

One of the most challenging cases in SHA is the evaluation of arid and semi-arid soils, which account for roughly one-third of the Earth's land surface (Abdelhak, 2022; Ayangbenro and Babalola, 2021). These soils are typically characterized by inherently low fertility, limited nitrogen and phosphorus, poor water-holding capacity, high pH, high salinity, and low soil organic matter (SOM) (Hag Husein et al., 2021; Mahajan et al., 2020), with coastal environments exhibiting severe constraints (Mahajan et al., 2021; Zhang et al., 2015; Bi et al., 2013). Therefore, the improvement of SHA in arid and semi-arid regions is crucial for food production and socio-economic development to support population growth, and to sustain environmental quality (Nazari et al., 2023; Bagherzadeh and Gholizadeh, 2018; Mandal et al., 2011). Although different SHA tools have been applied in arid and semi-arid climates, their applications were subjected to specific modifications, since they were initially developed for more humid and temperate climates and not dry climates (Ghimire et al., 2023; Gelaw et al., 2015). Furthermore, the Mediterranean basin, the most susceptible region to soil degradation and desertification (Ferreira et al., 2022), is a classic example of an arid and semi-arid area, also a sensitive hotspot to the ongoing climate change. In this pursuit, aggravated by population growth, food scarcity is becoming more severe, overwhelmingly burdening the agriculture sector (Aguilera et al., 2020; Matías et al., 2024). Contextually, many Mediterranean soils are approaching a critical state that threatens the sustainability of their ecosystems, limiting

economic growth and eventually impairing the sustainability and well-being of society (Ferreira et al., 2022). They are subjected to a xeric moisture regime (Verheye and de la Rosa, 2009) and extensive fertilizers use (Toth et al., 2016; Lado et al., 2008). In addition, they are often characterized by low SOM (Bel-Lahbib et al., 2023; Grilli et al., 2021; Stolte et al., 2016) or highly saline conditions in lowland areas (Colombani et al., 2024; Macumu et al., 2024). Consequently, Mediterranean agriculture is fraught with considerable difficulties due to the interplay of these factors (Martin-Sanz et al., 2024; Bel-Lahbib et al., 2023; AbdelRahman et al., 2022). For these reasons, a holistic SHA adapted to arid and semiarid soils, as well as the unique Mediterranean limitations, is strongly needed.

1.1. Soil health assessment tools

SHA tools are frameworks and methods that evaluate the functioning of the soil by integrating physical, chemical, and biological indicators into interpretable scores or indices, by employing field and laboratory assessment, and data analysis to enhance the balance of ecological relevance and sensitivity of the soil functioning and its health (Stott, 2019; Bünemann et al., 2018). However, the cost, labour, and accuracy of the scalability of the evaluation of the soil quality may depend on the modus operandi utilized (Sun et al., 2012, 2022). The Cornell's Comprehensive Assessment of Soil Health (CASH) is amongst the most widely applied SHA tools in North America (Hu et al., 2025a,b; Chahal and Van Eerd, 2019; Fine et al., 2017); with its index structure incorporated into many temperate European and Chinese studies (Makovníková et al., 2024; Jiang et al., 2023; Williams et al., 2020), because it integrates physical, chemical, and biological indicators into a holistic soil health evaluation (Jiang et al., 2023; Moebius-Clune et al., 2016). However, most of its physical and biological indicators are relatively costly and labour-intensive to measure, which can limit its scalability. The Soil Management Assessment Framework (SMAF) and CASH are the most widely cited and applied frameworks for SHA because of their flexibility in the formation of their MDS for SHA (Ye et al., 2021; Karlen et al., 2019; Lisboa et al., 2019). SMAF provides indicator scoring based on the soil functions and incorporates regionally informed soil and climate conditions, making it flexible and applicable across diverse management systems (Cherubin et al., 2017; Andrews et al., 2004). Similar to CASH, SMAF have been extensively applied in North America (Hu et al., 2025a,b; Trimarco et al., 2023; Stott et al., 2011), but it is also widely applied in Brazilian oxisols (Cherubin et al., 2017) and Mediterranean Turkish ecosystems (Reis and Dindaroğlu, 2024). However, some studies (e.g., Hu et al., 2025a,b) suggest that SMAF can be less sensitive than CASH in detecting differences associated with land use or management changes. On the other hand, CASH assessment is designed to be resilient to extreme values, but it requires regional adjustments to be accurate (Congreves et al., 2015; Chahal and Van Eerd, 2019), providing a standardized way to compare SH under different management systems (Zhang et al., 2024). The Haney Soil Health Tool incorporates microbial respiration, water-extractable carbon and nitrogen to represent the biological status of the soil (Haney et al., 2018). Because it relies on a smaller set of relatively inexpensive laboratory measurements, it is generally more sensitive to short-term management changes and cheaper than comprehensive frameworks such as SMAF and CASH, although its scalability and robustness across regions can be limited due to the strong environmental sensitivity of its biological indicators (Hu et al., 2025a,b; Chu et al., 2019). The Phospholipid Fatty Acid (PLFA) analysis is a widely used biological SH tool that provides detailed quantitative information about the soil microbial community beyond microbial biomass and respiration measurements (Buyer and Sasser, 2012). PLFA differentiates and quantifies major microbial functional groups, including bacteria, fungi, and actinomycetes, making it highly sensitive to changes in land use and management practices (Willers et al., 2015). However, PLFA is relatively costly, labour-intensive, and technically complex, requiring specialized

equipment and expertise (Frostegeard et al., 2011). As a result, it is not typically included in low-cost, routine commercial SH tests (Del Duca et al., 2025; Popa et al., 2023; Orgiazzi et al., 2017; Willers et al., 2015; Froger et al., 2024).

The main goal of this study is to provide a globally MDS for SHA, focusing on arid and semi-arid regions, which allows for strong cross-study comparability and methodological replicability. This study attempts to identify and weight the most representative physical, chemical, and biological indicators of soil functionality by combining data from a comprehensive systematic review. The final framework will include indicator weightings that may be used consistently across soil types, land uses, and management systems. In addition, particular emphasis is placed on the Mediterranean basin, a region highly vulnerable to multiple limiting factors and even aggravated by ongoing climate change.

2. Materials and methods

2.1. Systematic review search scheme

A comprehensive search scheme (Table 1) was developed to capture research relevant to the evaluation of SHA for agricultural suitability and productivity, particularly in arid and semi-arid environments. The focus was on research published between 2010 and 2025, aiming to capture contemporary studies that employed advanced methodologies and technologies. The developed search string was designed using three key pillars to warrant that the selected research articles adequately reported the goals of the systematic review. These pillars are.

- (a) Impacts of SH on agricultural or crop productivity.
- (b) SHA in arid and semi-arid regions, like that of the Mediterranean region.
- (c) SHA, unrelated to pollution from landfills and mining, or similar activities.

The search string retrieved a total of 4509 peer-reviewed articles, with 2678 and 1831 articles from Scopus and Web of Science, respectively. These articles were exported into the web-based tool Rayyan (<https://www.rayyan.ai>), which facilitates the simplification of systematic article screening. The validation of the string was subsequently performed by identifying benchmark articles (BA) within the study field of interest, which are reported in the Ofori et al. (2026) [Dataset]. BA verification is important for determining the efficacy of the search string in capturing germane studies and is representative of the topic in literature.

Table 1
Search coding and Boolean operators used for the systematic search.

Group	Keywords and Boolean operators
Soil	(soil OR land)
Soil Health Assessment	(assessment OR assessing OR suitability)
Soil Quality Indexes	(attribute OR parameter OR indicator OR propert*)
Study Areas	(mediterranean OR arid OR agricultur* OR crop)
Scoring	(weight OR index OR indices OR class OR score OR rating)
Irrelevant	(leaf OR LAI OR NDVI OR urban OR pollutant OR brownfield OR contamin* OR dump OR landfill)
Indicators	
Language	English
Document Type	Article, Review, and Book
Period	2010 to 2025
Subject Area	Agricultural and Biological Sciences, Environmental Science, Earth and Planetary Sciences, Engineering, Multidisciplinary, and Chemical Engineering

2.2. PRISMA protocol application and manuscripts inclusion for the minimum dataset selection

To have a more comprehensive knowledge about SHA tools and to prevent important information loss, a three-step protocol for manuscripts selection was carried out (Fig. 1). The first selection step comprises multiple procedures and adheres to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol (Fig. 1). These selections involved both inclusion and exclusion criteria (Table 2) at each stage, from the preliminary screening of titles and keywords, assessing abstracts, to the thorough reading of the entire articles, with a particular focus on soil parameters as reported in Andrews et al. (2004) and Stott (2019), to ensure the articles selected sufficiently address the research questions. Subsequently, 141 manuscripts were retrieved to be eligible at the end of the first selection step for further analysis. The 141 manuscripts were analyzed for the SHIs which they reported, and SHIs reported fewer than 20% were excluded from the MDS build-up, whereas MDS, highly reported (>20%) from the 141 manuscripts, were considered for further evaluation in the second step of manuscript selection. The second step was centred on manuscripts reporting a total dataset or MDS together with associated indicator weights, PCA communalities, or FA scores, which captured 70 manuscripts ("Manuscript (weights)" sheet in Ofori et al., 2026 [Dataset]). Within this step, the frequency of the considered SHIs from step 1 was re-evaluated, and indicators with frequency (<20%) were further excluded. The final criterion was centred on studies conducted in the Mediterranean basin reporting weights and communalities, which captured 17 manuscripts. Based on these, another 20% rule of thumb was applied to the SHIs considered from step 2. Indicators with frequency > 20% were finally retained for the MDS of this study. This last step was essential to ensure that the final MDS was identical at both global and Mediterranean scales, supporting its proposal as a standard and transferable MDS rather than a region-specific one. On the other hand, this separation of selection steps was also required to enable the subsequent extraction of SHIs weights, which was conducted ad hoc and independently at the global and Mediterranean scales using the corresponding subsets of manuscripts.

2.3. Weights extraction

The weights assigned to the SHIs included in the MDS are derived from the selected literature reporting weights, communalities, and FA scores (70 manuscripts for Global and 17 manuscripts for Mediterranean). For articles that provided communalities after PCA, the weights for each indicator in the MDS of that manuscript were manually calculated based on the communalities provided. Subsequently, they were reweighted based on the sum of communalities of the total SHIs considered in the specific manuscript. Similarly, for manuscripts that provided scores after FA, the weights of each indicator in the MDS of that manuscript were manually calculated based on the scores provided and reweighted based on the sum of factor loads. To complement the frequency-based selection criteria with empirical evidence on functional redundancy among candidate SHIs, the subset of reviewed articles reporting a PCA or Factor Analysis FA loading matrix (n = 74) was screened independently of the frequency-based screening. For each of these articles, the reported loading matrix (rotated or unrotated component/factor matrix) was examined for the co-occurrence of (i) indicators belonging to established SHI redundancy families and (ii) indicators that exceeded the 20% frequency threshold at the global scale but fell below it in the Mediterranean-specific subset used for final MDS selection, alongside any of the eleven indicators retained in the final MDS. For each pair of co-occurring indicators within the same loading matrix, the principal component (or factor) on which each indicator showed the highest absolute loading was recorded, together with the corresponding loading value as reported by the original authors. Two indicators were considered to display a co-loading (redundancy) signal

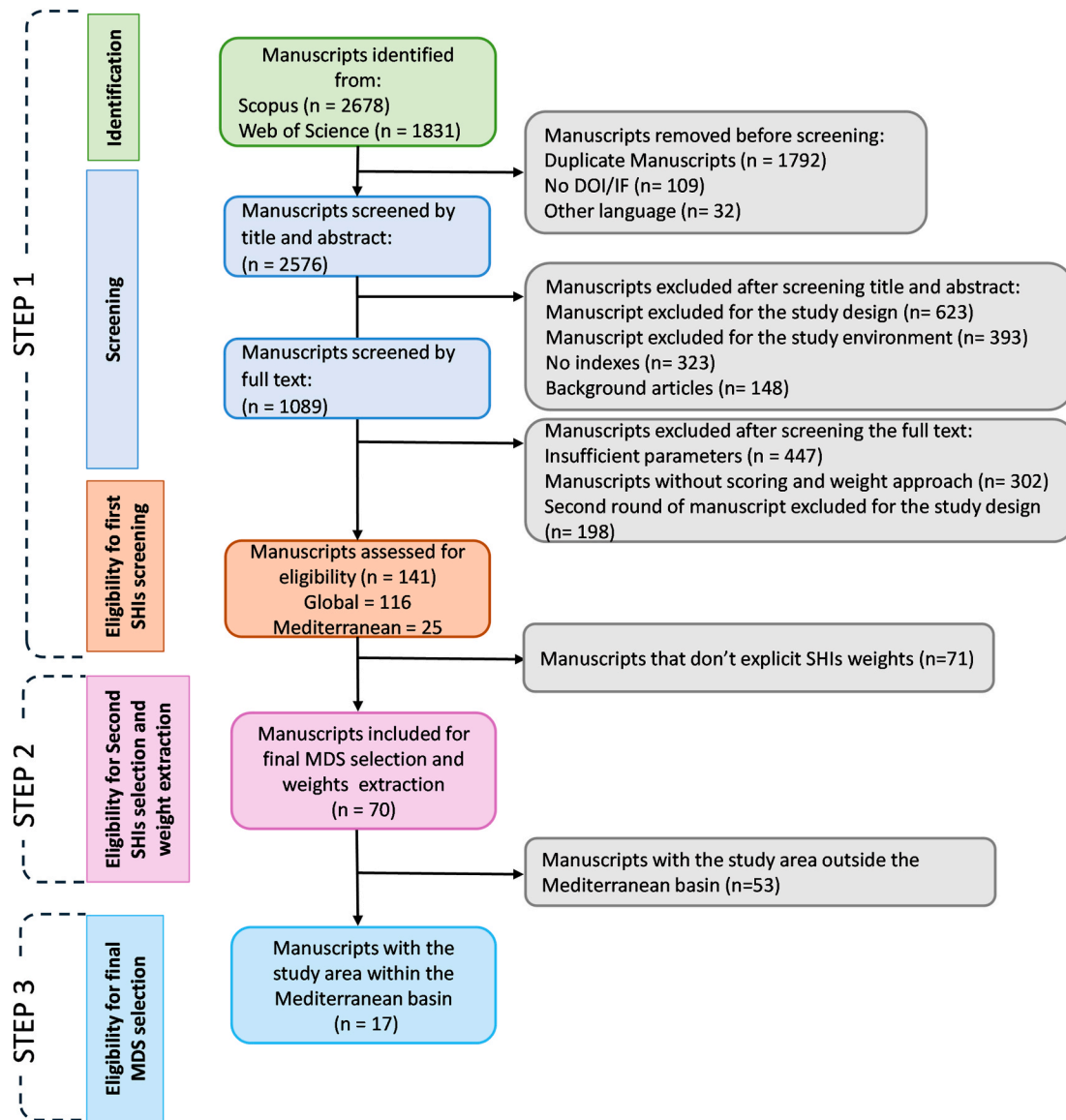


Fig. 1. Systematic Review Process Flowchart following the PRISMA protocol.

Table 2

Inclusion and exclusion criteria for the selection of the manuscripts.

Criteria	Included	Excluded	STEP
Removal of Duplicates, English Language, and Papers with DOI	Unduplicated manuscripts written in English with a DOI.	Duplicates and manuscripts without a DOI.	1
Screening of Abstracts and Titles	Rightly Studied Environment (Agriculture Suitability and Land Management)	Wrongly Studied Environment (Groundwater Salinization, Flooding, Soil Geotechnics, etc.)	1
In-depth Reading	Arid and semi-arid environments	Tropical and Arctic environments	1
Weighting Index	With a scores and weights approach	Without a scores and weights approach	1
Weights explication	With weight or communalities explication	Without weight or communalities explication	2
Mediterranean Area Focus	With a study area within the Mediterranean basin	Without a study area within the Mediterranean basin	3

when they shared the same highest-loading component; the proportion of co-loading was expressed both at the pair level (proportion of all comparable indicator pairs showing co-loading) and, for the indicators excluded from the final MDS, at the table level (proportion of loading matrices in which the excluded indicator co-loaded with at least one retained MDS indicator).

2.4. Statistical analyses

The final weights of the SHIs were estimated using a Bayesian approach with a non-informative Dirichlet distribution ($\alpha_i = 1$) (Gelman et al., 2013). The Expectation-Maximization (EM) algorithm was used to iteratively update the weights, starting with an initial uniform distribution (Kurihara and Welling, 2009):

$$w_i = 1/k \quad (1)$$

Where w_i is the weight related to the i SHI, and k is the total number SHIs considered in this study. The effective contribution (N_a) of each SHI was normalized in relation to k to limit the effects of manuscripts with partial data. The weights were initialized assuming a uniform weight vector $w^{(0)} = (w_1^{(0)}, \dots, w_k^{(0)})$. The missing share was reallocated proportionally

to the current weights of the unobserved SHIs, in accordance with standard Bayesian imputation procedures (Ruggieri et al., 2020). The observed and imputed contributions were stored in the sufficient statistics vector (C), and the weight vector was updated using the Bayesian procedure:

$$w^{(t+1)} = \frac{\alpha + C}{\sum_{i=1}^k (\alpha_i + C_i)} \quad (2)$$

Where α is the vector of SHIs concentration of the Dirichlet distribution, α_i is a pseudo-count indicating how much information is assigned to the SHIs a priori, $w^{(t+1)}$ is the new normalized vector weight of SHIs, calculated at the next iteration of the EM algorithm. The convergence was verified using the norm L^1 of the difference between successive weight vectors, defined as $\|w^{(t+1)} - w^{(t)}\|_1$, stopping the algorithm when the variation was less than 10^{-6} (Wang et al., 2022). This approach was run first on the global MDS extracted from all 70 articles and then applied to the 17 manuscripts referring to the Mediterranean Basin. To assess the robustness of the final SHI weights, two complementary analyses were conducted on both the global and the Mediterranean datasets. First, a hyperparameter sensitivity analysis was performed by re-fitting the EM algorithm over a full factorial grid combining pseudo-sample sizes ($N_0 = 20, 50, 100, 200, 500$) and Dirichlet concentration parameters ($\alpha = 0.1, 0.5, 1, 2, 5$). These grids span a 25-fold and 50-fold range, respectively, around the baseline values adopted in the main analysis. For each of the 25 $N_0 \times \alpha$ combinations, the resulting weight vector was compared to the baseline solution using the L_1 distance ($\sum |w_i(\text{grid}) - w_i(\text{baseline})|$) and the Spearman rank correlation between the two SHI rankings. Second, an article-level bootstrap was executed: the 70 source manuscripts, along with their associated records, were resampled with replacement 1000 times. Resampling was conducted at the manuscript level rather than the individual record level to preserve within-manuscript dependence, and the EM algorithm was re-fitted on each resample. This procedure yielded an empirical distribution and a corresponding 95% confidence interval for each final SHI weight. It must be stressed that both robustness analyses operate exclusively on the corpus of manuscripts from which the weights were extracted. Accordingly, the resulting confidence intervals quantify the uncertainty associated with the composition of the retrieved literature database, with which manuscripts happen to be included in the corpus, and with the choice of the hyperparameters of the Bayesian procedure, and not the measurement uncertainty of the underlying field and laboratory determined soil properties. No primary, field-level soil observation was resampled at any stage, and the weights reported hereafter must therefore not be regarded as validated against independent field data. To further evaluate whether the retained SHIs of the final MDS were affected by severe multicollinearity, Pearson correlation and variance inflation factor (VIF) analyses were performed on the literature-extracted indicator weight matrix used in the Bayesian weighting procedure. Because these weights represent, within each source manuscript, shares of that manuscript's own communality/loading budget, they constitute compositional data (Aitchison, 1982); applying Pearson correlation directly to such data could induce spurious correlations regardless of the underlying relationships between variables (Kronmal, 1993). A centred log-ratio (clr) transformation was therefore applied to each manuscript's reported indicator-weight sub-composition prior to computing pairwise Pearson correlations. VIF values were calculated as the diagonal of the inverse of the clr-corrected correlation matrix, restricted to the largest subset of SHIs for which every pairwise correlation was supported by ≥ 10 co-reporting literature records and for which the resulting correlation matrix was positive definite. A joint VIF across all 11 SHIs could not be computed due to the absence of manuscripts reporting all indicators simultaneously. Conventional thresholds were adopted for interpretation: $\text{VIF} < 5$ (no relevant collinearity), $5 \leq \text{VIF} < 10$ (moderate collinearity), and $\text{VIF} \geq 10$

(severe collinearity) (O'Brien, 2007).

3. Results and discussion

3.1. Spatial-temporal distribution of the manuscripts

From the 141 manuscripts globally analyzed on SH for arid and semi-arid environments, about 27 countries were captured, with major studies being made in China, the United States of America (USA), India, and Iran. With studies ranging from 19 to 24 in the above-mentioned countries, as shown in Fig. 2, this could be due to research efforts to tackle food security through soil amelioration, as these countries are the most densely populated in the world. For instance, studies in China are focused on areas intensely used for agriculture due to the flat fluvial fertile plains (Cao et al., 2023; Tian et al., 2020), black soils "Mellisols" (Dai et al., 2024; Yang et al., 2023; Chen et al., 2013), and in areas where agricultural productivity is challenged by dry climates combined to low soil fertility (Gao et al., 2025; Li et al., 2023; Li and Wang, 2023; Luo et al., 2017). Similarly, in the USA, most studies focused on areas with intense and mechanized agriculture coupled with management practices (Amorim et al., 2021; Bhardwaj et al., 2011; Nakajima et al., 2016), such as the irrigation from the Columbia River and its tributaries (DuPont et al., 2021), indicating the need to improve agriculture to sustain food security. The same patterns were also shared in studies based in India and Iran, focusing on areas with soils heavily subjected to highly limiting climatic conditions and intensive agriculture practices to enhance productivity to sustain the population's food demand (Ellur et al., 2024; Rukhsana and Molla, 2023; Vahidi et al., 2023; Nehrani et al., 2020; Paul et al., 2020; Rezaee et al., 2020; Zeraatpisheh et al., 2020; Nabiollahi et al., 2018; Bagherzadeh and Gholizadeh, 2016). In the Mediterranean context, Turkey and Egypt hosted most of the studies, which were focused on SH. The Turkish SH studies focusing on agricultural soils identified pH, Soil Organic Carbon (SOC), Electrical Conductivity (EC), and Bulk Density (BD) as key indicator constraints and needs amelioration to boost productivity in such a semi-arid environment (Acir and Gunal, 2020; Demir, 2024; Sargın et al., 2024; Reis and Dindaroğlu, 2024; Turan et al., 2019), as the sustainability of these soils is threatened due to land degradation (Karaca et al., 2021; Negiş and Şeker, 2020; Negiş et al., 2023). Meanwhile, in Egypt, the outcome from the studies on SH based on agricultural lands indicates that SOC, soil texture, soil salinity, Exchangeable Sodium Percentage (ESP) and pH were widely recognized in the existing literature as key indicators hindering agricultural productivity in the country (Abuzaid et al., 2021; Said et al., 2020; Selmy et al., 2021). Additionally, isolated studies in semi-arid and arid areas intensively used for agriculture in Africa and areas threatened with land degradation due to land management, highlighted SOC, Sodicity, texture, pH, and Cation Exchange Capacity (CEC) as the SHIs governing agricultural production (Damiba et al., 2024; Endrias et al., 2024; Leul et al., 2023; Adeniyi et al., 2017; Adeyolanu and Ogunkunle, 2016). Furthermore, the findings from some isolated studies in Latin America identify SOC as the most useful and critical indicator of soil quality (Aranguren and Cañón, 2023; Brar et al., 2023). Lastly, CEC, Salinity, pH, texture, Sodicity, and SOC were highlighted to be the constraints affecting agricultural productivity in arid and semi-arid environments in Central Europe (Juhos et al., 2019), the South Caucasus region (Jahany and Rezapour, 2020), and Iraq (Mohammed and Suliman, 2023) from the limited studies observed.

3.2. Minimum dataset selection

Over 138 soil indicators were identified from the 141 manuscripts studied, with most of these indicators being related to soil biochemistry. The stepwise MDS refinement provides, for the first time, a statistically grounded synthesis of the most recurrent and relevant SHI in the context of arid and semi-arid regions. The exclusion criteria based on representativeness levels were necessary to remove redundant or context-

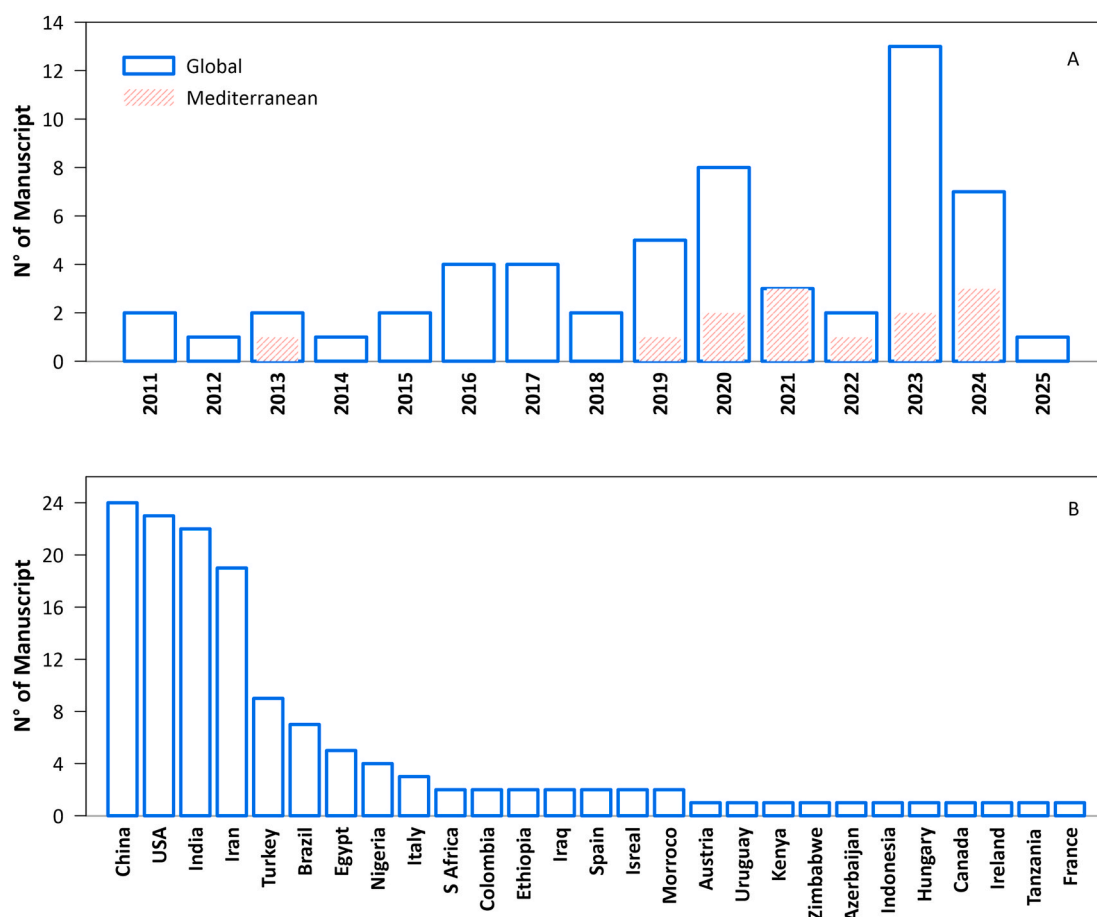


Fig. 2. A) Annual distribution of the manuscripts from 2011 to 2025 (Global studies in blue, Mediterranean studies in red); B) Distribution of manuscripts amongst countries.

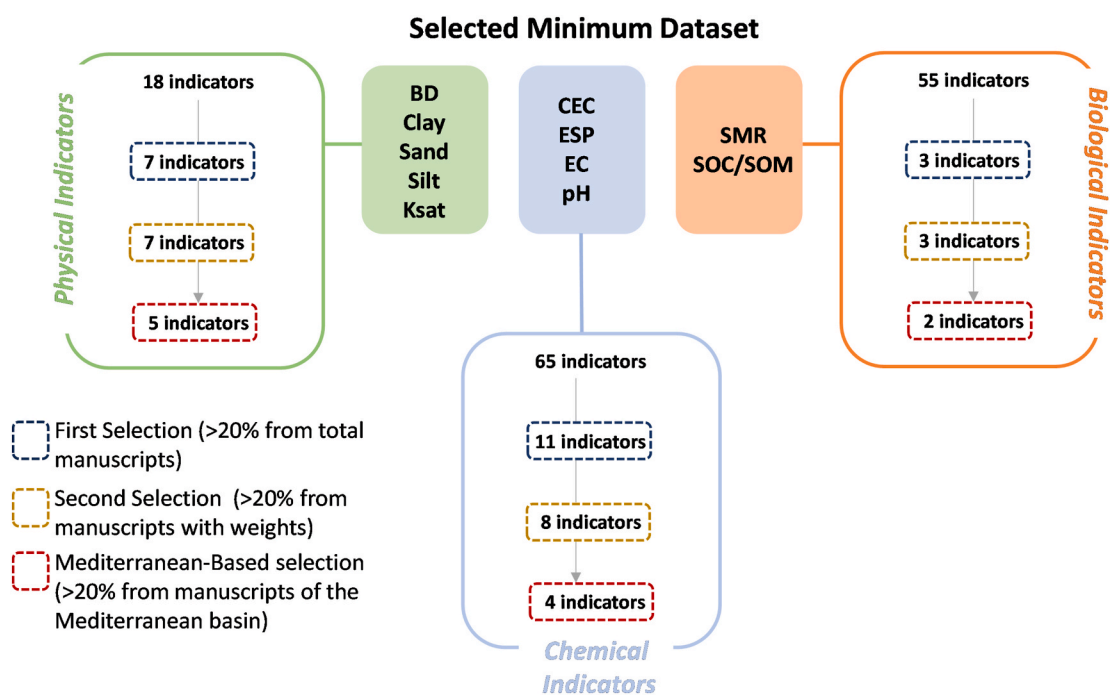


Fig. 3. Schematic diagram for the SHIs selection results. BD refers to bulk density, Ksat refers to saturated hydraulic conductivity, CEC refers to cation exchange capacity, ESP refers to exchangeable sodium percentage, EC refers to electrical conductivity, SMR refers to soil microbial respiration, SOC refers to soil organic carbon, and SOM refers to soil organic matter.

specific indicators. However, the dominance of physical indicators in the final MDS, particularly those related to soil texture, structure and porosity, reflects the central role of physical constraints in arid and semi-arid soils, where water infiltration and storage largely govern ecosystem productivity and resilience (Cardoso et al., 2013; Busico et al., 2023). Indeed, the application of the three selection criteria already exposed in the materials and methods section ended up with an MDS mainly formed by six physical indicators, four chemical indicators and two biological indicators (Fig. 3), as an appropriate MDS should comprise physical, chemical, and biological indicators (Gregorich et al., 1994). In fact, the first selection criteria application ended up with the exclusion of 11 physical parameters, 51 biological parameters and 55 chemical parameters ("Indicators Frequency_1st" sheet in Ofori et al., 2026 [Dataset]). In addition, the second selection criterion ended up with the exclusion of an additional 2 physical indicators, 1 biological indicator and 4 chemical indicators ("Indicators Frequency_2nd" sheet in Ofori et al., 2026 [Dataset]). Finally, the third selection criterion ended with the exclusion of an additional 4 chemical indicators and 1 biological indicator ("Indicator Frequency_3rd" sheet in Ofori et al., 2026 [Dataset]). Since the main goal of this study was to present a gold standard MDS for the SHA representative of soils in arid and semi-arid regions, the MDS was refined to the Mediterranean level in order to maintain consistency, and only the distribution of weight was calibrated differently between the worldwide assessment and the Mediterranean region assessment. Interestingly, the biological and chemical indicators were overall less frequently represented across the surveyed manuscripts, particularly in the Mediterranean studies, likely reflecting the higher methodological and procedural complexity associated to physical indicators. In addition, most of these SHIs are interrelated and perform similar functions in SHA but are reported differently by most researchers due to the laboratory protocols and reagents used in their measurements. Hence, the fractionation of these SHIs might have accounted for their low representations in this study, as various researchers may have determined these SHIs based on the reagents and instrumentation available to them. Significant biochemical indicators, such as Urease, Phosphatase, Catalase, Dehydrogenase, Sucrase, Aryl sulfatase, Arbuscular Mycorrhizal Fungi, Actinomycetes, and C/N had low frequencies in this study, probably due to instrumentation, cost, and time-intensive procedures in their determination, even though they are highly informative of soil biological activity and health (Dick et al., 1997; van Der Heijden et al., 2015; Tabatabai, 1994). For instance, measuring enzymatic activities, presents significant challenges regarding methodological complexity, technical requirements, and operating costs (Jiang et al., 2023). Biochemical indicators that require multi-step colorimetric or enzymatic assays, dedicated incubation, and specific reagents/instrumentation such as, urease activity (7.1%), dehydrogenase (8.5%), acid/alkaline phosphatase (5.0%/5.0%), catalase activity (4.3%), and aryl sulfatase (2.8%), were reported in fewer than 10% of the surveyed studies. First, enzymatic activities are extremely sensitive and require meticulous attention throughout the analytical process. For urease, for instance, the method involves incubating the soil sample with a specific substrate (often 200 mM urea) at 37 °C for 2 h, followed by the colorimetric determination of the NH_4^+ released during hydrolysis (Mahajan et al., 2021; Negiş and Seker, 2020; Raiesi, 2017; Raiesi and Kabiri, 2016). For phosphatase, the protocol utilizes disodium p-nitrophenyl phosphate as a substrate. This measurement must occur at a specific and strictly controlled pH: 11 for alkaline phosphatase and 6.5 for acid phosphatase. Incubation is conducted at 37 °C for 1 h, followed by a colorimetric reading (typically at 405 nm or 410 nm) to quantify the released p-nitrophenol (Martin-Sanz et al., 2024; Li et al., 2023; Sofi et al., 2016). Additionally, each assay should be performed in triplicate and accompanied by appropriate controls to account for any non-enzymatic product formation (Stott et al., 2013). For these reasons, the reviewed literature classifies enzymatic analyses among the most expensive methods within soil quality assessment, with studies explicitly describing them as costly and time-consuming. These high costs stem

from the required specialized labour, specific reagents, and lengthy laboratory incubation times. Consequently, due to the substantial analytical effort required, many researchers choose to exclude individual enzymes from the MDS (Jahany and Rezapour, 2020; Sheidai Karkaj et al., 2019; Paz-Kagan et al., 2014). Indeed, Benalcázar et al. (2024) reported that a complete analytical suite that includes advanced biological indicators incurs an estimated cost of approximately \$130 per sample. Conversely, selecting a MDS to mitigate analytical complexity can reduce costs to roughly \$60 per sample, yielding an estimated laboratory time savings of 6 h per sample. In addition, the Nitrogen pools (Mineralizable and Potential Mineralizable Nitrogen, Microbial Biomass Nitrogen, Water Soluble Nitrogen, NH_4^+ , NO_3^- , Hot-water Extractable Nitrogen, Solvita Labile Amino-Nitrogen, Alkaline Hydrolysable Nitrogen, and Available Nitrogen) are challenging to integrate into a single Nitrogen Index, as each indicator differs in chemical form, biological role, and turnover rates (Dodor et al., 2022; Soil Survey Staff, 2011; Juma and Paul, 1984). Therefore, their low representation in the scrutinized manuscripts was due to their fractionation, which may be a result of the instrumentation available to the researchers for their determination, since all these pools of N are challenging to assess in a single study. Similarly, the Carbon Pools (Active Organic Carbon, Labile Carbon, Particulate Organic Carbon, Readily Oxidizable Carbon, Water Extractable Organic Carbon, and Microbial Biomass Carbon) are challenging to be scientifically standardized as a single Carbon index, as each pool has different measurement methods, sensitivities, and ecological interpretations. This makes direct aggregation difficult, although they all represent fractions of SOC (Culman et al., 2012; Weil et al., 2003; Blair et al., 1995), and as such may have accounted for the lower representations in this study as they are all integral part of SOC. Furthermore, Exchangeable, Extractable, Available, and Total forms of (Fe, Mn, Zn, Na, Ca, Co, Cr, Mg, Mo, Si, B, and Pb) cannot also be aggregated due to the methods, reagents and instrumentation used in their determination; although they replicate similar functions in SHI, and each fraction represents a different geochemical pool or bioavailability level. Despite they all relate to soil nutrient status or contamination potential, their direct aggregation is scientifically inappropriate (Kabata-Pendias, 2000; Tessier et al., 1979). Hence, the fractionation and the highly site-specific characteristic of these SHIs may have accounted for their low representations in this study. Meanwhile, for physical indicators which were least reported comparatively, they had high frequencies of representation in this study, probably due to the ease, convenience, and availability of instrumentations for their measurement both on the field and in the laboratory compared to biological and chemical indicators (Bünemann et al., 2018; Doran and Parkin, 1994). Interestingly, CaCO_3 , commonly expressed as calcium carbonate equivalent (CCE), is a key chemical component of soils, particularly in calcareous and alkaline environments, where CCE standardizes various carbonate forms into a single measure. Calcareous soils are widespread across the Mediterranean basin due to the predominance of carbonate-rich parent materials (Laudicina et al., 2013; Zdruli et al., 2010). Although an alkaline soil pH frequently indicates the presence of free carbonates (Loeppert et al., 1984), soil pH reflects soil solution chemistry rather than carbonate reserves. Consequently, CaCO_3 /CCE is often correlated with, but not strictly redundant to soil pH; this explains the lower frequency of these indicators compared with the higher frequency of the pH measurements. Notably, in the subset of reviewed articles where both CaCO_3 /CCE and pH were jointly entered into a PCA, the two indicators loaded on the same principal component in 23.5% of cases, and when they did co-load, pH showed the higher loading magnitude. Consequently, pH was retained in the final MDS rather than CaCO_3 /CCE, reflecting its markedly higher reporting frequency across the reviewed literature and its broader functional role as a master variable governing nutrient availability, microbial activity, and metal speciation in soils, beyond the narrower informational content of carbonate content alone. Furthermore, one of the most widely used methods for determining CaCO_3 is the measurement of total alkalinity

by acid–base titration (Ahmad et al., 2023). This procedure involves the addition of precise amounts of reagent to the sample until a defined endpoint pH is reached. Standard acids, most commonly hydrochloric acid (HCl), are typically used as titrants, while endpoint determination is based on color indicators, particularly phenolphthalein and methyl orange. The endpoint is identified by the corresponding color change of the indicator. However, this method has several limitations, including the time required for the analysis and the discrepancy between the experimental endpoint and the true equivalence point (Wang et al., 2018). Notably, when CaCO_3/CCE was jointly entered into a PCA together with other indicators retained in the final, it co-loaded on the same principal component as at least one retained indicator in 64.7% of cases, most frequently with CEC and EC, in addition to pH, indicating that its informational content overlaps broadly with several physico-chemical indicators already included in the MDS, rather than with pH alone. This is consistent with CaCO_3/CCE showing the lowest reporting frequency among this group of chemical indicators in the global dataset (24.8%, only marginally above the 20% retention threshold), compared with pH (82.3%), EC (56.7%), and CEC (42.6%). This statistical redundancy, however, should not be read as evidence that carbonate content is functionally unimportant in the regions targeted by this MDS. Indeed, carbonate content heavily influences the solubility of micro-nutrients such as manganese (Mn) and zinc (Zn) (Juhos et al., 2019). In fact, high CaCO_3 levels can reduce the availability of these elements to plants (Lalitha et al., 2023). Furthermore, in calcareous soils, CaCO_3 is a key determinant of aggregate stability and, consequently, infiltration rates, thereby influencing root development and soil porosity (Karaca et al., 2021). Therefore, it is a valuable indicator for interpreting pH variations and nutrient solubility, providing insight into the paedogenic processes and chemical constraints typical of calcareous soils in dry environments. Consequently, for detailed analyses extending beyond the MDS, it serves as an optional, context-specific supplementary indicator to be measured and interpreted alongside rather than in place of pH for regional- or field-scale applications in known calcareous drylands. Furthermore, a comparable pattern emerges for other indicators commonly retained in previously published MDS but excluded from the present study, such as Available P, Available K, Available Zn, Total N, and Microbial Biomass Carbon (MBC), all of which passed the 20% frequency threshold at the global scale but fell below it in the Mediterranean-specific subset used for final selection. Mining the same set of PCA/FA loading matrices from the primary literature, each of these indicators co-loaded on the same principal component as at least one indicator retained in the final MDS in 48.5–75.0% of the cases in which it co-occurred with a retained. This convergent evidence, declining representativeness specifically in the Mediterranean subset combined with frequent co-loading with multiple retained physico-chemical indicators, indicates that the information carried by these excluded indicators is substantially, if imperfectly, captured by the combination of variables retained in the final MDS, reinforcing the parsimony of the proposed dataset beyond the frequency criterion alone. As a further, independent line of evidence regarding the internal collinearity structure of the final MDS, Pearson correlation and VIF analyses were performed on the literature-extracted indicator weights. Because these per-manuscript weights are compositional, the raw pairwise correlations were, as expected, strongly inflated by closure, and the resulting correlation matrix was not positive definite. After the required clr transformation, this artifact was substantially reduced, confirming that the raw estimates did not reflect genuine relationships between the underlying SHIs. VIF, computed on the largest naturally well-conditioned subset of SHIs with adequate literature co-reporting (BD, Clay, pH, CEC, and SOC), remained below the conventional threshold for severe collinearity ($\text{VIF} = 10$) for all five indicators (Table 4), with Clay showing the highest value ($\text{VIF} = 6.75$), consistent with the well-documented pedological relationship between clay content and cation exchange capacity. For the remaining six SHIs (Sand, Silt, Ksat, EC, ESP, and SMR), the number of manuscripts jointly

reporting the required indicator pairs was too small ($n < 10$ for most of the pairs, Table 4) to allow a statistically robust joint VIF estimate. It must therefore be stressed that the present analysis demonstrates the absence of severe multicollinearity only within the BD, Clay, pH, CEC and SOC subset, whereas the collinearity structure of the remaining six indicators cannot be quantified with the currently available literature database, so that a residual information redundancy among them cannot be ruled out. Within this scope, and together with the PCA/FA co-loading evidence reported in Table 3, the available results do not provide any indication of severe multicollinearity affecting the final 11-indicator MDS; a conclusive assessment, however, will require a primary dataset in which all the 11 indicators are measured on the same set of samples.

3.3. Bayesian analysis of weights

The Bayesian calibration of indicator weights improves the framework by quantifying the relative contribution of each SHI on a global and Mediterranean scale. In the global dataset, the most relevant parameters were SOC (0.147), BD (0.119), EC (0.111) and CEC (0.106) (Fig. 4). Texture indicators (Clay, Sand, and Silt) showed intermediate weights (0.082, 0.061, 0.057), whilst Ksat had a marginal weight (0.023). This can be attributed to the high spatial and temporal variability of Ksat, which is characterized by coefficients of variation often ranging between 27% and 75% (Damiba et al., 2024; Sinha et al., 2013). This instability is strongly influenced by management practices such as tillage, which significantly alters pore size distribution. In this context, intensive soil processing can initially increase porosity, but in the long term they tend to destabilize the aggregates, leading to the formation of surface crusts and the sealing of the pores, drastically reducing permeability (Oliveira et al., 2024). In addition, conservation practices such as Sodo and Mulch-tillage promote the development of a more stable soil structure and increase Ksat over time compared to processed systems (Zou et al., 2021). The absence of physical disturbance, in fact, allows the preservation of macropores and biopores created by roots and fauna. On the contrary, trampling of livestock can increase bulk density and reduce Ksat due to compaction, especially near animal concentration points. However, in some Mediterranean grassland settings, moderate grazing has been associated with local increases in conductivity related to changes in soil composition (Paz-Kagan et al., 2014). Additionally, Ksat shows profoundly different dynamics and values between irrigated agricultural lands (such as rice paddies and croplands) and rain-fed drylands (rainfed drylands), due to opposing management objectives and natural degradation processes. In certain systems, such as rice paddies, low hydraulic conductivity is an intentional management goal, achieved through puddling, to maximize water-use efficiency. In fact, rice fields show the lowest conductivity values overall, with values ranging from 0.08 cm/h to 0.70 cm/h (Rezaee et al., 2020; Sofi et al., 2016). Here, the absence of vegetation cover led to phenomena such as surface sealing and crusting, caused by raindrop impact on bare soils,

Table 3

Summary of the Principal Component Analysis (PCA)/Factor Analysis (FA) co-loading analysis performed on the subset of reviewed articles reporting a numeric loading matrix.

Excluded Indicator	Global Frequency (Mediterranean Frequency)	% of co-loadings
CaCO_3/CCE	22.9% (17.6%)	64.7% with CEC, EC, pH
Available P	31.4% (17.6%)	48.5% with pH, SOC, EC
Available K	28.6% (17.6%)	71.2% with CEC, Clay, BD, SOC
Available Zn	24.3% (5.9%)	55.6% with CEC, Clay, SOC
Total N	41.4% (17.6%)	75.0% with BD, SOC, pH, Clay
MBC	22.9% (17.6%)	66.7% with SMR, BD, SOC

Table 4

Pairwise Pearson correlation matrix (r , lower triangle) among the 11 retained MDS indicators, computed after centred log-ratio (clr) transformation of the literature-extracted indicator. Values in parentheses indicate the number of literature records in which each indicator pair was jointly reported. Significance markers (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$) are shown only for pairs supported by ≥ 10 co-reporting records; † denotes correlations estimated from fewer than 10 records. Variance Inflation Factor is reported only for the subset of indicators (BD, Clay, pH, CEC, SOC) for which the clr-corrected correlation matrix was naturally positive definite with adequate literature co-reporting.

	BD	Clay	Sand	Silt	Ksat	pH	EC	CEC	ESP	SOC	SMR
BD	—										
Clay	−0.55* (n = 20)	—									
Sand	0.20 (n = 16)	−0.38 (n = 25)	—								
Silt	0.15 (n = 15)	−0.47* (n = 21)	0.32 (n = 20)	—							
Ksat	−0.68* (n = 10)	0.23† (n = 9)	−0.40† (n = 8)	−0.21† (n = 8)	—						
pH	−0.64*** (n = 34)	0.25 (n = 23)	−0.40 (n = 19)	−0.63** (n = 17)	0.13 (n = 12)	—					
EC	−0.57 (n = 12)	−0.36 (n = 13)	−0.05† (n = 9)	−0.03† (n = 9)	0.41† (n = 8)	−0.17 (n = 40)	—				
CEC	−0.25 (n = 21)	0.72** (n = 17)	−0.37 (n = 14)	−0.76** (n = 11)	−0.29† (n = 9)	0.12 (n = 29)	−0.54* (n = 19)	—			
ESP	0.82† (n = 7)	−0.95† (n = 6)	0.74† (n = 6)	0.58† (n = 5)	−0.98† (n = 5)	−0.67* (n = 11)	0.07 (n = 11)	0.38† (n = 9)	—		
SOC	−0.10 (n = 37)	0.45* (n = 29)	−0.76*** (n = 22)	−0.70*** (n = 19)	0.01 (n = 13)	−0.18 (n = 59)	−0.31 (n = 35)	−0.02 (n = 30)	−0.65† (n = 9)	—	
SMR	0.90† (n = 4)	0.27† (n = 9)	−0.55† (n = 6)	−0.94† (n = 3)	n.a. (n = 1)	−0.16† (n = 7)	0.37† (n = 5)	−0.20† (n = 5)	n.a. (n = 1)	−0.31 (n = 11)	—
VIF	2.56	6.75	n.a.	n.a.	n.a.	1.9	n.a.	3.94	n.a.	2.45	n.a.

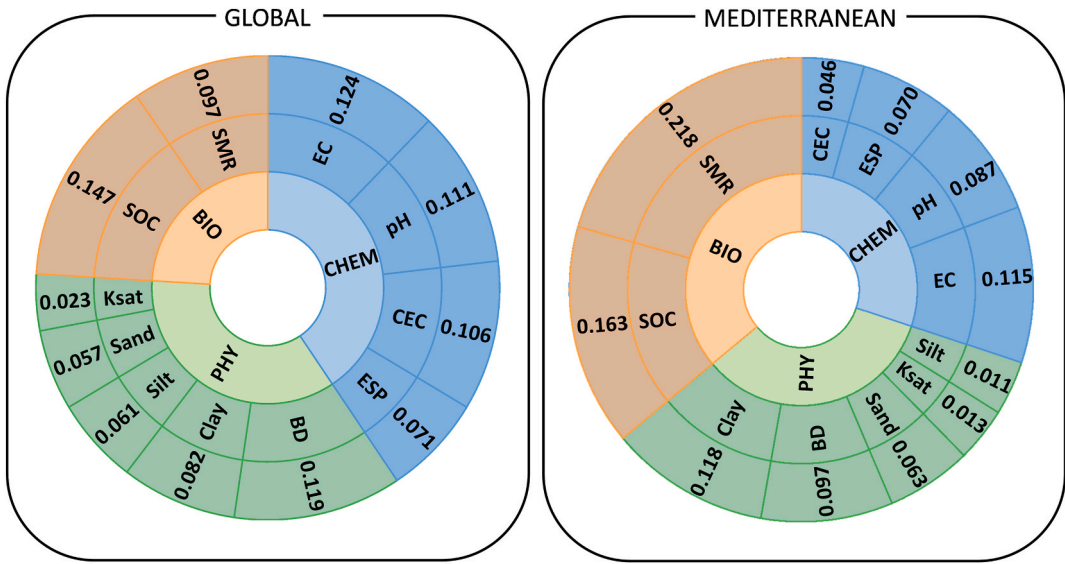


Fig. 4. Pie charts with the final Bayesian weights of all the (Global and Mediterranean) the SHIs of the MDS. BIO refers to the biological SHIs, PHY refers to the physical SHIs, and CHEM refer to the chemical SHIs.

drastically reduce permeability (Negiş et al., 2023; Mahajan et al., 2020; Mandal et al., 2011). In fact, although potentially higher than rice fields, the values reflect environmental stress: in dry farming areas in Turkey the average is 0.54 cm/h (Sargın et al., 2024), while in semi-arid Indian soils there are averages of 1.73 cm/h (Vasu et al., 2016). These dynamics made point measurements poorly representative of actual soil functionality over time (Oliveira et al., 2024; Toth et al., 2024; Sillero-Medina et al., 2020). Consequently, assigning a universally high weight to this indicator may be inappropriate, as its interpretation depends strongly on land-use practices and management objectives (Rezaee et al., 2020; Sofi et al., 2016). On the other hand, in the Mediterranean dataset, the distribution is more polarized. SMR is dominant (0.218), followed by SOC (0.163) and Clay (0.118). CEC (0.046) and pH (0.087) are lower than the global dataset, while Silt showed a quite negligible weight (0.011). This is due to the fact that silt particles are

particularly susceptible to selective removal through water and wind erosion processes, which are common in Mediterranean cultivated lands (Bel-Labbib et al., 2023; Leul et al., 2023; Negiş et al., 2023). Additionally, its vulnerability is reinforced by the characteristic wetting-drying regime of Mediterranean climates, in which summer desiccation cracking is followed by the slaking of the dry aggregates under autumn torrential rainfall (Çelik et al., 2021; AbdelRahman et al., 2022). Because silt lacks the strong organo-mineral bonding capacity of clay, its aggregates are less resistant to these forces, leading to a rapid decline in aggregate stability. Consequently, this parameter reflects structural fragility and vulnerability to erosion rather than positive functional capacity, as seen with clay or SOM. In fact, compared to clay or SOM, silt has a negligible impact on nutrient retention (Nath et al., 2024; Karaca et al., 2021). In Mediterranean environments, where soil health is primarily governed by microbial dynamics and aggregate

stability, silt can be considered negligible (Martin-Sanz et al., 2024; Bi et al., 2013). The analysis of the observed/imputed relative contributions (Fig. 5) underline significant differences between the two datasets. On the global level, the indicators with the largest observed shares include SOC (0.164), BD (0.137) and EC (0.128). However, SMR and CEC have large imputed shares (0.092 and 0.063, respectively), implying that the algorithm relies more on estimations in the absence of comprehensive data. The paucity of data for these indicators compared to other MDS indicators is driven by a combination of technical, economic, and methodological factors that make these parameters less accessible (Tian et al., 2020; Paz-Kagan et al., 2014). In fact, SMR requires the use of gas chromatography or titrimetric methods following extended incubation periods, ranging from 24 h to several weeks, to quantify the released CO₂ (Samaei et al., 2022; Rekik et al., 2018). For CEC, standard measurement involves cation displacement methods (typically using ammonium acetate) that are technically complex (Rezaee et al., 2020). Furthermore, the subsequent analysis of the extracted cations often requires expensive analytical instrumentation, such as inductively coupled plasma atomic emission spectroscopy (ICP-AES) or inductively coupled plasma mass spectrometry (ICP-MS) (Purakayastha et al., 2019). This interpretation is further supported by a characteristic analysis of the included literature. Missingness of SMR was consistently high across publication decades (80–100%), countries (67–100%), and journals (67–100%), with no subgroup showing markedly lower missingness. This consistent pattern indicates that the issue is more likely attributable to a widespread technical limitation rather than a region or venue specific reporting gap. In contrast, missingness of CEC varied more substantially by country (88% in Turkey vs. 40% in the USA, based on studies included in this review), suggesting that, beyond analytical complexity, differences in routine soil monitoring practices across regions may also contribute to its underrepresentation. The significance of SOC, EC, and CEC underscores the strong

relationship between SOM dynamics, ionic balance and nutrient retention capacity as essential factors of the total soil performance (Saxton and Rawls, 2006; Bastida et al., 2008). The results obtained on the Mediterranean dataset showed a more polarized weighting pattern. Indeed, in the Mediterranean basin, SMR and SOC not only have the highest final weights, but also a significant observed component (SMR = 0.220; SOC = 0.193), emphasizing their empirical centrality. However, SMR has the largest imputed share (0.189), demonstrating that direct data, although important, are frequently insufficient and must be inferred. This apparently ambiguous result stems from the fact that SMR, although reported in only 10 of the 17 Mediterranean manuscripts (and in 15 of the 70 manuscripts forming the global subset), was consistently assigned a high relative weight in the studies that did measure it. It should be stressed that the observed component of the SMR weight is therefore supported by a limited number of direct measurements, whereas its imputed component derives entirely from the redistribution of the missing probability mass and does not constitute independent empirical evidence. Accordingly, only two statements can be safely drawn from the reviewed literature on an empirical basis: i) where SMR is actually measured in Mediterranean studies, it consistently receives a high relative weight, and ii) SMR is reported far less frequently than the physicochemical indicators. The precise numerical value of its final weight, on the other hand, must be regarded as an evidence-informed estimate rather than as a directly measured quantity. Clay exhibits similar behaviour: high weight (0.118), significant observed share (0.133), and non-negligible imputations (0.062). This pattern highlights the biological sensitivity of Mediterranean soils, where microbial activity is an important proxy of soil functionality. Contextually, Mediterranean soils are typically subjected to thermic and xeric regimes (Verheye and de la Rosa, 2009), high soil salinity (Selmy et al., 2021), and low SOM content (Reis and Dindaroğlu, 2024), consistently limiting the microbial activity in response to all the imposed

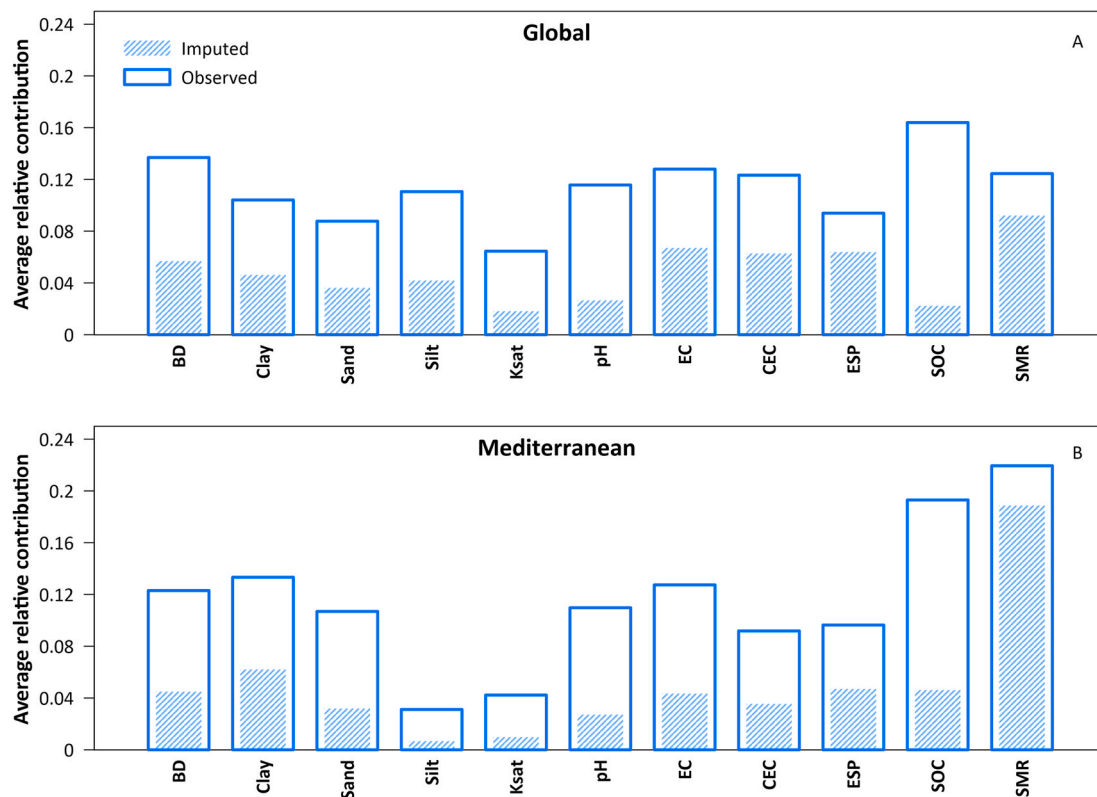


Fig. 5. Bar chart of the average relative and imputed contributions A) Global and B) Mediterranean for the SHIs of the MDS. Observed and imputed relative contributions for each manuscript are provided in “Bayesian Analysis (Global)” and “Bayesian Analysis (Med)” sheets of the Ofori et al. (2026) [Dataset] for the global and Mediterranean datasets, respectively.

limiting factors (Curiel Yuste et al., 2007). The co-dominance of these two indicators reflects the strong biotic-abiotic connection typical of Mediterranean agroecosystems, where biological processes rapidly respond to short-term variations in soil moisture and salinity (Morrison et al., 2017). In Mediterranean environments, where prolonged summer drought, high temperatures and intensive land use exert strong pressures on soil functioning, biological indicators respond to disturbance far more rapidly than most physicochemical properties, which change slowly or reflect cumulative degradation, for this reason, microbial parameters are commonly regarded as early responders to soil stress and are increasingly incorporated into comprehensive soil health assessments (Çelik et al., 2021; Sillero-Medina et al., 2020). This behaviour is mechanistically well established for Mediterranean-type climates: upon summer desiccation, part of the microbial biomass undergoes osmotic stress and cell lysis, and the labile intracellular compounds released, together with the SOM previously protected within disrupted aggregates, become rapidly available to the surviving community upon autumn rewetting, producing pronounced flushes of CO₂ and mineral nitrogen (Fierer and Schimel, 2003). In a Mediterranean cork oak woodland, a single 18-mm rainfall event following summer drought increased soil CO₂ efflux by approximately 15-fold within hours, releasing roughly 18 g C m⁻² over the following 10 days (Jarvis et al., 2007), while extracellular enzyme activities responded to the same regime with enzyme-specific dynamics, distinct from the microbial biomass response itself (Daou et al., 2016). However, it should be stressed that this evidence is derived from independent primary studies and not from the weights estimated here, the EM procedure redistributes probability mass among indicators and cannot, by itself, support any inference on microbial behaviour. Additionally, current European soil health frameworks, including the EU Soil Strategy for 2030, the proposed EU Soil Monitoring Law, the EU Mission “A Soil Deal for Europe”, and monitoring initiatives such as LUCAS Soil and the European Soil Observatory, recognize soil biodiversity as a core component of soil health and promote the inclusion of biological indicators alongside physical and chemical metrics for soil assessment (DuPont et al., 2021; Armenise et al., 2013). This reflects the transition from a predominantly agronomic view of soil as a substrate for plant production to a broader ecological perspective that recognizes soil as a dynamic living ecosystem. Within this paradigm, soil health is defined not only by its capacity to sustain crop productivity but also by its ability to support biodiversity, regulate biogeochemical cycles, maintain ecosystem

functions, and deliver a wide range of ecosystem services (Lehmann et al., 2020; Ferrarini et al., 2018). However, the analysis of observed/imputed weights reveals critical methodological insights. Besides SMR and SOC displaying high empirical relevance, they also exhibited a significant imputed contribution, indicating a persistent lack of information about the role of biological parameters in SHA in the actual literature. However, the two proposed Global and Mediterranean MDS overcome this limitation using the Bayesian approach with a non-informative Dirichlet distribution coupled with the EM algorithm, since the missing share calculated for each manuscript is redistributed on the missing indicators, and the weights were updated and fixed iteratively until the difference between successive weight vectors was almost null.

The final global and Mediterranean SHI weights were robust to both evaluated sources of uncertainty (Fig. 6). Only Ksat exhibited a visible, though still modest, departure from its baseline value, which occurred at the combination of the smallest pseudo-sample size and the highest Dirichlet concentration parameter tested. The article-level bootstrap confirmed this robustness under sampling uncertainty, where sampling uncertainty is here understood as the uncertainty arising from the specific set of manuscripts retrieved by the systematic review, and not as the field-scale measurement uncertainty of the individual soil properties. When the 95% confidence intervals of two SHIs do not overlap, their weights can be considered significantly different, indicating that this ranking is stable regardless of which specific manuscripts are included in the analyzed sample. In contrast, overlapping intervals indicate that the fine-grained ordering of two adjacent SHIs cannot be considered entirely robust to the composition of the source literature. Applying this criterion, the confidence intervals of the four highest-ranked SHIs (SOC, EC, BD, pH) did not overlap with those of the five lowest-ranked SHIs (Clay, ESP, Silt, Sand, Ksat) for both the datasets. However, the Mediterranean weight vector was estimated from a substantially smaller literature base, the resulting 95% confidence intervals were markedly wider across all SHIs and SMR displayed the largest bootstrap uncertainty consistent with its comparatively sparse reporting and its correspondingly large imputed weight share. This confirms that the separation between the highest- and lowest-ranked parameters reflects a genuine feature of the pooled evidence rather than an artifact of the specific set of retrieved manuscripts. In contrast, confidence intervals overlapped extensively among adjacent, similarly ranked SHIs indicating that their relative fine-grained ordering should be interpreted with caution. However, the

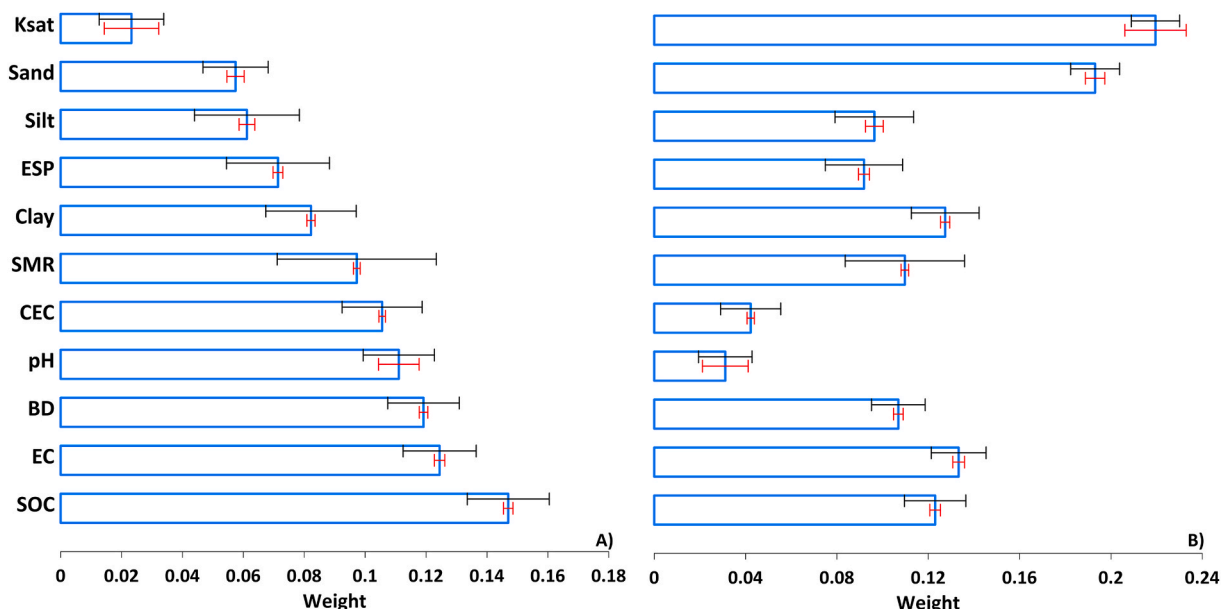


Fig. 6. A) Global and B) Mediterranean SHI weights (bars) with 95% bootstrap confidence intervals (black line) and hyperparameter sensitivity range (red line).

sensitivity and bootstrap analyses presented here indicate that this redistribution step does not introduce an artifactual dependence on arbitrary statistical analysis choices. The relative ranking of the 11 SHIs, which underlies the selection of the proposed MDS, remained unchanged across a wide range of pseudo-sample sizes, and the magnitude of the final weights varied only modestly under resampling of the source literature.

3.4. SHIs aggregation proposal

Some of the MDS indicators obtained in this study can be grouped into coherent sets based on their capacity to provide more comprehensive and integrated information on key soil functional features (Fig. 7). This is because, when considered individually, some parameters describe only partial aspects, while when combined, they allow for a better understanding of the soil function to be represented, such as the ability to support plant growth, water regulation, or resistance to compaction (Andrews et al., 2004). This approach adheres to existing practices in the development of composite indices and SH measures, where aggregating related variables eliminates redundancy and improves interpretability (Singh et al., 2023). For instance, soil texture parameters, BD, and Ksat can be shaped together for building a compaction/sealing aggregated score since all together describe the conditions that affect plant's root development within the soil (Lipiec and Hatano, 2003; McQueen and Shepherd, 2002). Similarly, EC, ESP, and pH may be integrated into a single salinity–sodicity–acidity composite score, providing a concise representation of the dominant chemical constraints affecting soil quality (Omuto et al., 2020). While SOC, SMR and CEC describe independent soil chemistry and ecological properties and they can be individually used as scores in a SHA equation. It should be stressed that, at this stage, the CS and SSA groupings are proposed on process-based grounds rather than empirically validated. Indeed, it should be stressed that the CS and SSA groupings reflect relative indicator weights within the overall MDS framework, rather than standardized, unit-consistent composite scores computed at the individual soil sample level. Translating these weighted groupings into a fully operational scoring equation, analogous to the scoring curves adopted by SMAF and CASH, will require dedicated calibration against field-measured outcome variables, such as crop productivity and soil degradation status, collected under consistent sampling and analytical protocols. Such empirical calibration, extending beyond the literature-based scope of the present study, represents a necessary next step to operationalize the CS and SSA groupings as fully quantitative diagnostic tools of soil health status. However, a broader body of literature showing that composite soil quality/health indices generally track crop yield and functional soil status more robustly than standalone indicators (Li et al., 2023; Nazari et al., 2023; Singh et al., 2023; Nabiollahi et al., 2020; Mei et al., 2019; Luo et al., 2017). For instance, in studies conducted on tropical soils, the aggregate physical subgroup revealed that physical degradation was the main factor limiting root

growth and reducing yields and providing priority management guidance (Cherubin et al., 2017, 2021). Therefore, an aggregate index in this context captures the overall physical barrier that plant roots must overcome to access water and nutrients (Leul et al., 2023; Gura and Mkeni, 2019). Furthermore, in arid and semi-arid environments, the combined evaluation of EC, ESP, and pH is essential for understanding soil degradation processes. Although individual pH or EC values may not indicate critical conditions, their integration into an integrated index can reveal sodicity conditions that degrade soil structure and substantially reduce permeability (Ellur et al., 2024). Additionally, in salt-affected soils, parameters such as EC, ESP, and pH interact to limit plant growth. The detrimental effects of salinization cannot be fully understood by considering these factors individually. Instead, an aggregate index that reflects the overall salinity-related stress provides a more accurate predictor of crop yield loss (Mahajan et al., 2021).

3.5. Towards a climate-driven recalibration of the MDS: a speculative outlook

Under the climate trajectories outlined for the Mediterranean Basin and other arid and semi-arid regions, characterized by rising temperatures, declining precipitation, and increasing evaporative demand (Lazoglou et al., 2024), the relative diagnostic power of individual SHIs, and therefore their MDS weights, is expected to evolve. A relevant strength of the Bayesian weighting procedure adopted in this study rely on explicitly designed for dynamic recalibration as new evidence accumulates; consequently, future studies conducted under intensified drought and heat stress would not require a conceptually new framework, but would instead update the current global and Mediterranean weight vectors through revised communalities and factor loadings. However, several process-based trajectories can be anticipated in a speculative manner. Reliance on irrigation, fertilizer application, and land reclamation is expected to increase across these regions as aridity intensifies (Naorem et al., 2023; Carvalho et al., 2022; Fader et al., 2016), while salinization is likely to be reinforced through evapoconcentration of salts under elevated evapotranspiration, seawater intrusion driven by groundwater abstraction, upconing of saline groundwater, and the increasing reliance on marginal-quality irrigation water and treated wastewater (Mousavi et al., 2026; Almazan-Benitez et al., 2024; Mastrocicco and Colombani, 2021). Furthermore, a geo-statistical survey of eleven soil properties across a hot arid region reported EC as by far the most spatially variable indicator, an order of magnitude greater than pH and appreciably greater than SOC, underscoring its intrinsically higher discriminatory potential under water-limited conditions (Nogiya et al., 2024). Consistently, spatio-temporal monitoring of a drip-irrigated saline field showed a soil EC increasing of 20% across a single irrigation-drying cycle, driven by evapoconcentration during the dry phase (Zheng et al., 2009). Since elevated soil EC directly constrains microbial activity and nutrient cycling (Yang et al., 2025; Zhang et al., 2019; Wichern et al., 2006), an

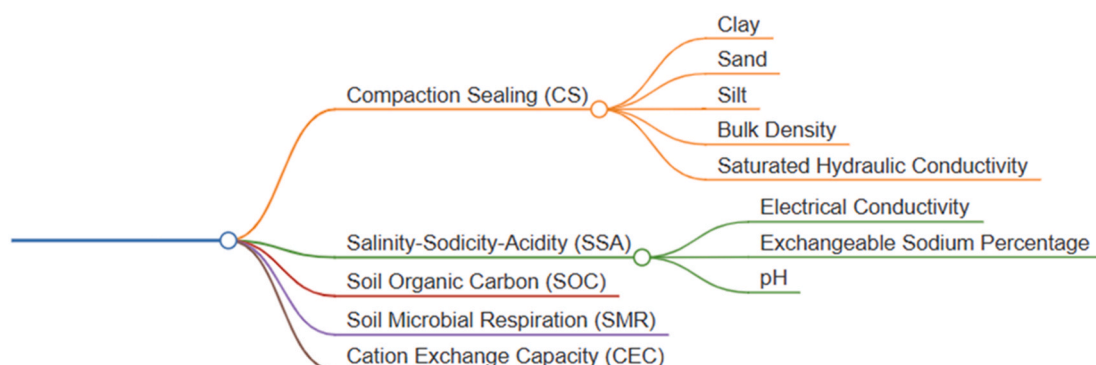


Fig. 7. Illustrative mark map of how the single SHIs could be grouped in aggregated scores.

increase in its between-site variance across future primary datasets would most probably translate into higher weight for EC. [de Paul Obade and Lal \(2016\)](#) compared a meteorological drought year (2012) with a normal year (2013) in Ohio to quantify changes in parameter importance. Drought drastically altered the influence of parameters on soil quality, with SOC and EC identified as the most significant parameters influencing SQI during water stress. Furthermore, a high absolute difference in factor weights for SOC and EC was observed between the drought and drought-free years, indicating that the sensitivity of these indicators increases under climate stress. SOC already holds the highest global weight and the second-highest Mediterranean weight, reflecting its established centrality as a proxy for soil functionality. However, its response to drought intensification is highly heterogeneous, depending on local soil properties, land-use history, and management or amelioration practices ([Arije et al., 2024](#)). Persistent SOC losses have already been documented across several arid and semi-arid regions ([Abebaw and Feleke, 2026](#); [Luo et al., 2020](#); [Lal, 2004](#)), and a generalized decline could reduce the between-site variance of SOC, thereby lowering rather than raising its future communality-based weight, despite its process-based importance. Additionally, SOC variability is significantly influenced by climatic gradients and vegetation stress, with coefficient of variations (CVs) typically increasing under less favourable environmental conditions. [Vasu et al. \(2024\)](#) in a study across a climo-sequence from semi-arid to sub-humid climates, showed that the CV for SOC was approximately 59.93% in surface horizons and 61.16% in subsurface horizons. In India, for example, SOC variability fluctuates with different climatic characteristics. Reported SOC CV values range from 21.91% in more stable to 42.57% in zones with higher climatic variability ([Nath et al., 2024](#)). In addition, a long-term soil warming experiment in a temperate forest showed that legacy effects of decade-long warming persisted even after the treatment was suspended: SOM content and water holding capacity (WHC) remained significantly reduced relative to control plots ($-0.184 \text{ g SOM g}^{-1}$ and $-0.82 \text{ g H}_2\text{O g}^{-1}$ in the O horizon, respectively), with the SOM decline accounting for up to 62% of the observed WHC reduction, illustrating a self-reinforcing feedback whereby warming-induced SOC losses further compromise soil water buffering capacity ([Werner et al., 2020](#)). Conversely, the empirical weight of SMR, already dominant in the Mediterranean dataset but affected by the largest imputed share, would most probably strengthen as more direct microbial activity measurements become available from climate-stressed sites, since salinity and heat-driven suppression of microbial communities ([Yang et al., 2025](#); [Zhang et al., 2019](#)) would increase its discriminatory value between degraded and resilient soils. For SMR, a global meta-analysis of 187 field warming experiments reported an average 11.8% increase SMR that scaled positively with warming magnitude in short-term trials ([Yang et al., 2023](#)), while a meta-analysis of manipulative drought experiments reported reductions in microbial respiration resistance ranging from -17.5% in agricultural soils to -64.0% and -65.5% in forest and grassland soils, respectively, with SOC content, clay content and pH identified as the main regulating factors of this magnitude ([Amarasinghe et al., 2024](#)). The substantially larger and more context-dependent response to drought than to warming is consistent with SMR's already-high imputed uncertainty in the Mediterranean subset of the present dataset and supports its candidacy for weight strengthening as more direct measurements accumulate. Soil pH is expected to follow a more context-dependent trajectory. Insufficient rainfall to leach base cations (Na^+ , Ca^{2+} , Mg^{2+} , K^+), combined with evapoconcentration of soluble salts and carbonates, generally favours progressive alkalisation in arid and semi-arid soils ([Naorem et al., 2023](#); [Rengel, 2011](#)), a trend that may be further intensified under future warming. However, this is not a uniform response: repeated application of ammonium-based fertilizers can locally acidify soils through H^+ release during nitrification ([Buthelezi and Buthelezi-Dube, 2022](#)), while drainage of coastal reclaimed soils with pyritic, peat-rich horizons may induce acidification via pyrite oxidation a ([Ofori et al., 2025](#)) site-specific process rather than a regional trend.

Given this bidirectionality, pH is unlikely to show a systematic weight increase at the global scale, though it may still gain relevance within specific Mediterranean coastal settings. Taken together, these considerations suggest that under intensifying drought and heat stress, EC and SMR are the SHIs most likely to gain relative weight in future MDS recalibrations, SOC would probably retain a high but possibly reduced weight due to more homogeneous degradation across sites, and pH would remain comparatively stable at the global scale while regionally variable. It should be stressed that these trajectories are speculative and should be treated as hypotheses to be tested as the underlying literature base expands, rather than as a modification of the weights reported in this study. It is also important to distinguish climate response pathways between salinized drylands and non-saline inland drylands. In arid salinized zones, which include coastal ecosystems and inland oases, soil quality evolution is dominated by salt dynamics and evapotranspiration. Global warming accelerates evaporation, triggering the capillary rise of salts from surface aquifers into the active root layer. In coastal areas, this path is aggravated by salt intrusion due to sea level rise. In these systems, EC and ESP show an increasing trend during drought and post-monsoon periods, while heavy rainfall acts as a temporary “washing” mechanism. The EC is the most critical and variable indicator in the quality indices (SQI) of these areas ([Mahajan et al., 2020, 2021](#)). Furthermore, high ESP causes aggregate dispersion, dramatically reducing permeability and Ksat by creating anoxic conditions and physically hinders root growth ([Ellur et al., 2024](#); [AbdelRahman et al., 2022](#)). It is therefore expected, in arid saline regions, that the EC will show the most marked weight gain, directly reflecting the processes of evapoconcentration, salt intrusion and capillary rise already described previously, consistent with global projections identifying these contexts, including parts of the Mediterranean, South America, South and Western Australia, and coastal North Africa, as future salinization hotspots ([Hassani et al., 2021](#)). Regarding SMR, sensitivity is expected to be highest in salinized drylands, where salinity and water stress act as summing stressors rather than acting independently on microbial communities ([Yang et al., 2025](#); [Zhang et al., 2019](#)), a non-additive interaction directly demonstrated in a controlled incubation experiment, where taken individually both salt stress and drought increased microbial carbon biomass and soil respiration, but their combination significantly reduced cumulative CO_2 emissions compared to each stress taken in isolation ([Qadeer, 2022](#)), a result consistent with what was observed for OM decomposition, where the combination of drought and salinity further reduced the decomposition of plant residues compared to each stress taken individually ([Qadeer et al., 2024](#)). In salt-free inland drylands, the climate response focuses on OM loss and vulnerability to erosion. Reduced rainfall and rising temperatures accelerate the mineralization of OM, reducing aggregate stability and making soil more susceptible to water and wind erosion ([Luo et al., 2017](#)). In this context, SOC is the universal “proxy” indicator ([Hamidi Nehrani et al., 2020](#)). In scenarios of intensive management or degradation, it shows a constant downward trend, while in paths of secondary succession or rural abandonment in the Mediterranean, it tends to gradually accumulate over the decades ([Martin-Sanz et al., 2024](#)). BD can also increase due to loss of organic structure and pressure from machinery or trampling, reducing pore space ([AbdelRahman et al., 2022](#)). Hence, in the absence of salinity, the main constraint becomes physical degradation.

3.6. Comparison with CASH and SMAF selection, scoring and weighting criteria and general limitations of the proposed MDS

As outlined in Section 1.1, SMAF and CASH rely on site-adjusted or regionally calibrated scoring functions, which, while ecologically meaningful, makes intra- and inter-study comparison challenging. The SMAF provides validated scoring algorithms for approximately 13 physical (BD, aggregate stability, AWC, water-filled pore space), chemical (pH, EC, SAR, extractable phosphorus and potassium) and biological (SOC, microbial biomass carbon, potentially mineralizable

nitrogen, β -glucosidase activity) indicators, drawn from a substantially larger pool of candidate soil properties, with general guidance recommending a minimum of five indicators spanning all three domains (Karlen et al., 2019; Andrews et al., 2004). The CASH protocol typically applies a standard package of 12 to 15 physical (texture, wet aggregate stability, AWC, surface and subsurface penetration resistance), biological (SOM, active carbon, ACE soil protein, SMR) and chemical (pH, extractable phosphorus and potassium, minor elements) indicators, with an extended assessment menu offering up to 39 possible measurements (Chahal and Van Eerd, 2019; Congreves et al., 2015; Moebius-Clune et al., 2016). Direct overlap between the proposed 11-indicator MDS and the core indicator sets of SMAF and CASH is limited to approximately four indicators in each case (BD, pH, EC, and SOC/SOM). Conversely, several indicators considered core to both general frameworks are absent from the proposed MDS. Furthermore, the proposed MDS retains several indicators that are secondary or absent in the core sets of SMAF and CASH: the full texture fractionation, Ksat, CEC, and ESP (rather than the SAR used by SMAF and CASH). This divergence reflects the different environmental focuses of the frameworks: SMAF and CASH were developed primarily for temperate, largely non-saline agricultural soils in North America, and consequently emphasize management-responsive organic matter and biological activity indicators. In contrast, the present dual-scale MDS was derived specifically from arid and semi-arid areas where salinity, sodicity, and hydraulic/textural constraints are comparatively more diagnostic of soil functional status, and SMR was retained as the sole, yet regionally dominant, biological indicator. Notwithstanding these differences in scope and calibration domain, the comparison between proposed MDS and existing literature reveals a substantial degree of convergence between the proposed MDS and both general frameworks and regionally focused studies, indicating that a common physicochemical core underlies soil health assessment irrespective of climatic setting. BD, pH, electrical conductivity and SOM are retained, in some form, in virtually every framework examined, including SMAF, CASH and all the regional MDS studies considered here, confirming their role as first-order, cross-context indicators of soil health. This convergence is particularly evident when the proposed MDS is benchmarked against watershed-scale applications of SMAF in Mediterranean settings: Reis and Dindaroğlu (2024), applying SMAF to a semi-arid Mediterranean watershed in Turkey, selected a nine-indicator MDS (BD, aggregate stability, TOC, pH, EC, available phosphorus, available potassium, AWC and water-filled pore space). Four of these nine indicators (coincide exactly with indicators retained in the present MDS, corresponding to an overlap of approximately 44%. An even closer correspondence is observed with the digital soil mapping-based MDS proposed by Zeraatpisheh et al. (2020) for deforested and intensively cultivated soils in Iran, which retained SOC, CEC, CCE, pH and EC as its final five-indicator dataset. Four of these five indicators are shared with the present MDS, yielding an overlap of 80%, among the highest recorded across the studies reviewed. Conversely, direct comparison also highlights systematic differences. Comparable divergence is observed in dryland SMAF/SQI applications in the Negev Desert, Israel (Levi et al., 2020, 2022), where a 12–14 indicator soil quality index built around sand, clay, SOM, pH, EC, SAR, and phosphorus similarly shares only its physicochemical core (texture, pH, and EC) with the proposed MDS. Likewise, a SMAF-based application to treated-wastewater-irrigated cropland near Urmia, Iran (Qubo et al., 2025) retained an 8-indicator MDS dominated by heavy-metal contamination indicators (Cd, Pb, and available Zn) alongside BD, EC, OM, available P, and SAR, reflecting a pollution-focused research question distinct from the general soil functionality focus of the present study. However, the approach adopted in this study introduces both conceptual and methodological advancements. Consequently, this study is geared to a MDS that can be widely used in arid and semi-arid regions to promote replicability. For this reason, MDS selection was centred on relatively user-friendly, easily accessible and cost-effective indicators and, above all, was set up to allow comparability between different

studies (Moebius-Clune et al., 2016; Scharenbroch and Catania, 2012; Halvorson et al., 1996). Moreover, through Bayesian weighting, this study provides a quantitative foundation for dynamic recalibration, enabling the integration of new data as they become available. The resulting framework thus serves as a “gold standard” for harmonizing arid and semi-arid SHA globally while accounting for regional ecological specificity, although presenting a MDS that provides a less detailed assessment of SH compared to both SMAF and CASH.

3.7. Limitation of the proposed MDS

Several limitations of the present framework deserve explicit acknowledgment. First, the proposed MDS was derived entirely from published literature and has not yet been validated against independent, field-level experimental data. The reported indicator weights therefore reflect patterns synthesized across heterogeneous secondary sources rather than measurements obtained under controlled or harmonized sampling protocols. Consistently, the bootstrap confidence intervals reported in Section 3.3 describe the stability of the weights with respect to the composition of the literature corpus, and must not be interpreted as a field-scale validation of the proposed MDS. This limitation is particularly relevant for SMR, which displays the largest imputed component among all the retained indicators: across the 17 Mediterranean manuscripts, the mean imputed contribution assigned to SMR is 0.189, a value of the same order of magnitude as the mean observed contribution computed over the 10 manuscripts that actually reported it (0.220). In other words, a substantial fraction of the final Mediterranean SMR weight (0.218) does not derive from reported measurements, but from the redistribution of the missing probability mass. It should be stressed that Bayesian imputation is a statistical estimation technique that redistributes the missing weight share on the basis of co-reported evidence available in the source literature and cannot substitute direct, empirically measured microbial respiration data; the high ranking of SMR in the Mediterranean dataset should therefore be interpreted with due caution, particularly in view of the consistently high missingness of SMR measurements observed across the reviewed literature. Second, the indicator weights reported here represent an aggregate signal pooled across a wide range of pedoclimatic and management contexts and should not be assumed to be invariant across them. As discussed above, Ksat variability alone spans coefficients of variation of 27–75% and is governed by contrasting mechanisms in rainfed versus irrigated systems, while soil texture directly constrains structural stability and erodibility. It is therefore expected that the relative importance, and hence the posterior weights, of individual SHIs would shift under different soil textures, tillage regimes, and irrigation management, none of which could be resolved as separate strata in the present analysis given the limited number of manuscripts reporting these covariates in a consistent, extractable format. The same constraint applies to the diagnostics of internal redundancy: since no manuscript reported all the 11 retained indicators simultaneously, the multicollinearity assessment could be completed only for a five-indicator subset (Section 3.2), and the acquisition of a primary dataset covering the full MDS remains a prerequisite for a conclusive evaluation. Third, and relatedly, the goal of this study was to set a general MDS for arid and semi-arid environments without taking into account land-use types, such as annual croplands, perennial orchards, and grasslands, each of which is associated with markedly different disturbance regimes, root system architectures, and OM input pathways that could plausibly alter the relative diagnostic value of individual SHIs. Given the limited number of manuscripts available for each individual soil type and land use, weight vectors could not be reliably stratified beyond the global and Mediterranean scales adopted in this study. The proposed MDS should therefore be regarded as a generalized, literature-derived framework intended to act as a flexible backbone for further, more specific refinement, rather than as a finished, field-validated scoring tool. Future studies should focus on site-specific calibration using field-collected

data across contrasting soil textures, tillage and irrigation regimes, land-use types, and climatic settings, in order to test and refine the robustness, and where necessary the transferability, of the proposed weighting scheme.

4. Conclusion

This study provides a globally harmonized and statistically robust framework for SHA in arid and semi-arid regions, derived from a systematic review of 141 manuscripts. By reconciling indicator selection and Bayesian weighting at both global and Mediterranean scales, the proposed MDS overcomes the lack of comparability that limits existing SHA approaches, while remaining sensitive to region-specific soil constraints. This dual-scale perspective makes the framework particularly relevant for the Mediterranean basin, where soil degradation and climate change pressures demand harmonized yet locally meaningful assessment tools. Future developments should move along three concrete directions. First, the weights derived here should be used to calibrate a composite soil health scoring equation and validate it in the field, comparing predicted scores with independent agronomic productivity data at representative pilot sites in the Mediterranean basin, thus bridging the empirical validation gap recognized as the limitation of the present study. Within this validation effort, the Mediterranean ranking of SMR should be given priority, since it is the indicator, whose weight relies to the greatest extent on the redistribution step rather than on directly reported measurements. Second, the speculative weight recalibration trajectories under climate stress proposed in Section 3.5, in particular the expected weight gain of EC and SMR and the possible weight reduction of SOC by inter-site homogenization, should be subjected to empirical verification as new primary datasets from sites under intense climate stress become available, exploiting the dynamic recalibration capability intrinsic to the Bayesian EM procedure developed here. Third, as soon as the number of available manuscripts by individual soil type, land use, and salinity status is sufficient, weights should be adapted by stratified subgroups to further refine the framework's regional sensitivity, including in support of the implementation of emerging regulatory frameworks such as the European Union's Soil Monitoring Law.

CRedit authorship contribution statement

Abraham Ofori: Writing – original draft, Data curation, Conceptualization. **Luigi Alessandrino:** Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Tiziana Danise:** Writing – review & editing, Data curation. **Gianluigi Busico:** Writing – review & editing, Methodology, Conceptualization. **Nicolò Colombani:** Writing – review & editing, Conceptualization. **Vassilis Aschonitis:** Writing – review & editing, Validation, Conceptualization. **Simona Castaldi:** Writing – review & editing, Validation, Conceptualization. **Micòl Mastrocicco:** Writing – review & editing, Validation, Supervision, Resources, Conceptualization.

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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2312, 2023 Section 1 Farming IA).

Data availability

Data are available in the Mendeley Data repository.

[Integrating systematic review and Bayesian weighting to derive a minimum dataset for soil health assessment in arid and semi-arid regions \(Original data\)](#) (Mendeley Data)

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