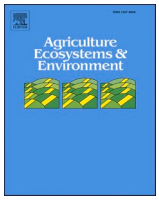
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Soil biological quality across land-use gradients: An arthropod-based index from a comprehensive literature review

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ABSTRACT

Biological indicators are increasingly used to assess soil health, yet global reference values remain scarce for most metrics. The QBS-ar index (Soil Biological Quality based on arthropods), which evaluates the degree of adaptation of soil microarthropods to edaphic conditions, is now widely applied, but comparative benchmarks across ecosystems and regions have been lacking. This study presents a global meta-analysis of QBS-ar, synthesizing 826 observations published between 2002 and 2025 across 16 countries and seven major land-use categories. Data were extracted and standardized by land use, management system, and disturbance type, and analysed using non-parametric methods. QBS-ar values ranged from 0 to 417 (mean: 110). Forests, vineyards and orchards, and grasslands showed the highest values, whereas agricultural and urban areas consistently exhibited lower scores. Organic agriculture performed significantly better than conventional and no-tillage systems, underscoring the positive effects of reduced chemical inputs and enhanced organic matter. Severe disturbances—including contamination, mining, and historical military activity—were associated with the lowest values. Spatial patterns indicated substantial geographic variability linked to land-use intensity and site history. To facilitate interpretation, we developed *QBS-ar explorer*, an interactive tool that positions user-provided values within the global distribution of published data. By providing the most comprehensive dataset and analysis of QBS-ar to date, this study establishes an essential international reference framework for interpreting soil biological quality. The results highlight both the sensitivity of QBS-ar to ecological gradients and anthropogenic pressures and the need for methodological standardization—particularly in EMI classification—to enable robust global comparisons and to support the development of reliable benchmarks for soil health assessment.

1. Introduction

1.1. Soil health and the complexity of quality assessment

The concept of Soil Health has gained global traction, with the management of healthy soils now recognized as a worldwide objective. Soil quality is a fundamental component of environmental quality, alongside air and water quality (Andrews et al., 2002). It extends beyond the notion of soil contamination and is broadly defined as "the capacity of a soil to function within ecosystem and land-use boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health" (Bünemann et al., 2018). This definition reflects the complexity and site-specific nature of belowground ecosystems and highlights the intricate links between soil functions and the ecosystem services they support. In fact, soil quality is inherently more complex than air or water quality—not only because it includes solid, liquid, and gaseous phases, but also because soils serve a broader range of ecological and anthropogenic functions (Nortcliff, 2002). Soil quality can be assessed in both agroecosystems, where productivity is the primary (though not exclusive) ecosystem service, and in natural ecosystems, where maintaining environmental integrity and conserving biodiversity are key objectives (Bünemann et al., 2018).

Intrinsic factors such as parent material, climate, topography, and hydrology heavily influence the potential range of soil properties, making the establishment of universal threshold values impractical—at least in absolute terms. As such, soil quality assessment must incorporate baseline or reference values to effectively evaluate the impact of management practices (Bünemann et al., 2018). A critical component of such assessments is identifying sensitive soil attributes that reflect the soil's functional capacity and can serve as reliable indicators of quality.

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1.2. Biological indicators in soil monitoring frameworks

Effective soil health metrics evaluate aspects of ecosystem function such as biogeochemical cycling, nutrient availability, and ecological resilience. Within this framework, biological soil parameters offer critical insights for land use and management decisions (Bispo et al., 2009; Bispo and Oliveira, 2007; Muñoz-Rojas, 2018; Pulleman et al., 2012). Land use practices, the intensity and frequency of anthropogenic disturbances, and the quantity and quality of organic matter inputs (e.g., via vegetation) are all key determinants of soil biodiversity (Nunes et al., 2020). Consequently, biological monitoring is increasingly recognized in both academic and policy domains as essential to understanding soil quality across spatial and regional scales.

The scientific relevance of any soil health indicator depends on several criteria: (i) its sensitivity to management-induced changes; (ii) strong correlation with beneficial soil functions and with variables that are otherwise difficult to measure; (iii) its ability to elucidate ecosystem processes; (iv) its comprehensibility and utility for land managers in decision-making; and (v) ease and affordability of measurement (Parisi et al., 2005). Soil fauna is a fundamental component of terrestrial ecosystem health, playing critical roles in nutrient cycling, organic matter decomposition, and plant productivity (Menta and Remelli, 2020). Current methods for assessing soil quality using mesofauna generally fall into two categories: general evaluations of microarthropod communities (Parisi, 2001) and assessments based on specific taxa (Paoletti and Hassall, 1999; Parisi and Menta, 2008). A mature soil ecosystem may harbor thousands of animal species and an even greater diversity of microbial taxa, yet less than 1% of soil organisms have been classified to date (Bonilla-Bedoya et al., 2023). Indeed, species-level identification of soil organisms remains a major bottleneck (Bünemann et al., 2018).

1.3. The QBS-ar index: an ecomorphological approach

To address this limitation, Parisi et al. (2005) developed the QBS-ar index (Soil Biological Quality, based on arthropods), which assesses the degree of adaptation of soil microarthropods to the edaphic environment rather than relying on species richness or diversity. Adaptations such as depigmentation, reduction of visual structures, streamlined bodies with compact appendages, and reduced abilities for locomotion (e.g., flying or jumping), along with diminished water retention capacity (e.g., thinner cuticle, absence of hydrophobic compounds), are all considered in assigning eco-morphological scores (Parisi et al., 2005). By classifying organisms into morphotypes according to these traits, the QBS-ar provides a practical, morphology-based indicator of soil biological quality. The trajectory of the QBS-ar index reflects a clear progression from a novel theoretical proposal to an institutionalized global monitoring framework. This evolution can be categorized into four distinct developmental phases:

1. Foundational phase (2001–2005): The index was first formalized by Vittorio Parisi in 2001, proposing a paradigm shift in soil quality assessment by prioritizing ecomorphological adaptation over complex taxonomic identification. This phase culminated in the foundational validation by Parisi et al. (2005), which established the index as a robust tool for sensitive soil health monitoring.
2. Institutionalization and networking (2017): A pivotal milestone occurred in 2017 with the establishment of the National Working Group on QBS-ar within the Italian Society of Soil Science (SISS, “SISS:: QBS-ar,” 2026). This initiative transformed a localized methodology into a structured network of more than 50 experts, dedicated to the coordination, implementation, and quality control of the index. The group now has more than eighty experts, mostly Italian, but with some from other European countries or beyond.
3. Expansion and standardization (2018–current): The subsequent years saw the first global-scale synthesis (Menta et al., 2018) and a concerted effort toward methodological harmonization. During this period, the SISS Working Group began cataloging hundreds of morphotype images to address inter-observer variability and identify key opportunities, such as the index's inclusion in agricultural certification protocols like the "Biodiversity Alliance".

The QBS-ar offers a standardized, bioindicator-based approach for assessing soil ecological condition by examining the diversity and adaptive traits of soil microarthropods, and its adoption has grown considerably over the last ten years.

1.4. Position of QBS-ar in soil health assessment

QBS-ar offers a unique mid-range resolution between high-sensitivity microbial assays and functional macrofauna monitoring. The inclusion of QBS-ar in the Soil Monitoring Law as a Soil Descriptor of soil biodiversity loss has been a major step forward for the application of the index in an integrated way with other systems for assessing soil health and degradation (Office of the European Union L- and Luxembourg, 2025). To address the current landscape of soil health monitoring, it is essential to distinguish the operational focus of QBS-ar from other established biological and biochemical metrics. While QBS-ar targets the long-term structural integrity of the soil habitat through microarthropod adaptation, other indices—such as microbial quotients and enzymatic activities—provide higher temporal resolution for monitoring immediate shifts in nutrient cycling and carbon sequestration potential (Table 1).

Table 1
Comparison of QBS-ar with established soil biodiversity and quality indicators: operational focus, strengths, and limitations.

Index	Target group	Primary strength	Primary limitation	Bibliography
QBS-ar	Microarthropods	High sensitivity to physical habitat structure and land-use intensity.	Qualitative (presence/absence); lacks direct trophic resolution.	(Galli et al., 2021; Parisi, 2001)
Microbial Indices (Cmic:Corg)	Bacteria/Fungi	Early predictors of C sequestration and N availability; sensitive to tillage.	High seasonal/climatic variability; requires precise lab equipment.	(Anderson and Domsch, 1989; Marinari et al., 2022)
Nematode Maturity Index	Nematoda	Reflects energy channels (bacterial/fungal) and food web maturity.	Requires high taxonomic expertise	(Bongers, 1990; Urzelai et al., 2000)
QBS-c	Collembola	Sensitive to soil amendments (e.g., biochar) and micro-environmental health.	Subject to seasonal moisture fluctuations and population "blooms."	(Gruss et al., 2019; Parisi and Menta, 2008)
Gamasine Maturity Index	Predatory Mites	Tracks top-predator stability and long-term airborne pollution.	Low specimen counts in intensive agricultural soils.	(Čoja and Bruckner, 2006; Ruf, 1998)
QBS-e	Earthworms	Assesses macro-engineering (porosity and drainage).	Limited in dry/sandy soils; sensitive to fungicides.	(Fusaro et al., 2018; Paoletti et al., 2013)

The QBS-ar index is particularly informative for assessing habitat stability. Unlike microbial-based indicators that react to transient pulses (e.g., fertilization), the eco-morphological adaptations of micro-arthropods reflect the long-term physical integrity of the soil matrix and the presence of micro-refugia. It is the ideal tool for large-scale monitoring due to its cost-effectiveness and moderate taxonomic requirements.

On the other hand, QBS-ar is less effective than nematode indices or microbial assays for detecting subtle changes in nutrient cycling or early-stage metabolic shifts. Furthermore, in systems where specialized biodiversity is at risk, but habitat structure remains intact, a dominance-based metric like the Berger-Parker index provides a more sensitive signal of community impairment.

1.5. Knowledge gaps and the role of meta-analysis

While the QBS-ar index has seen a proliferation in use over the last two decades, several critical bottlenecks have impeded its transition from a local bioindicator to a global monitoring tool: (i) absence of standardized benchmarks: until now, practitioners lacked a statistically robust "global mean" or "reference range" to determine whether a specific score reflects high or low quality within a given land-use context, (ii) methodological heterogeneity: there is a lack of clarity regarding how EMI scores are applied across different geographic regions, which complicates the comparability of results, (iii) lack of cross-ecosystem synthesis: most studies are site-specific; a lack of large-scale comparisons across ecological and anthropogenic gradients has prevented the identification of universal trends in soil fauna adaptation to land-use intensity. A meta-analysis is the only appropriate tool to address these gaps because it allows for: (i) scaling, it transcends the limitations of individual site-specific studies to capture the variance inherent in different climatic and edaphic conditions, and (ii) harmonization, by extracting and standardizing many observations into the same land-use and disturbance categories, we can test the sensitivity of the index to specific pressures (e.g., organic vs. conventional farming) at a global scale.

This contribution advances the field significantly beyond previous syntheses. The dataset spans a broad latitudinal and longitudinal gradient, with a primary focus in Europe and supplementary data from South America and Asia. Considering that in recent years this index has become widely used at the international scale, it is necessary to conduct this meta-analysis to allow a pooled evaluation of the data produced so far and to identify a reference category for defining soil quality and soil health across different ecosystems and land uses. The objective of this study is to move beyond descriptive local assessments by synthesizing two decades of QBS-ar data into a quantitative international reference framework. While the QBS-ar index is increasingly adopted, it lacks a standardized international protocol for EMI assignment. This study does not aim to fill this gap and, as consequence, we include all published values to prevent subjective filtering bias, thus establishing a baseline that reflects the actual methodological landscape of the discipline. By analysing QBS-ar values in relation to land use, disturbance types, and agricultural practices, this study aims to address the need for baseline and reference values and to: (1) identify spatial patterns in soil biological quality; (2) explore the ecological impacts of various land uses and disturbances; (3) evaluate the potential of QBS-ar as a landscape-scale indicator of soil health; (4) provide a standardized comparative tool for stakeholders to contextualize soil biological quality across global ecological gradients

2. Materials and methods

2.1. QBS-ar index: a brief methodological recall

Soil Biological Quality index based on arthropods (QBS-ar) was calculated following the protocol established by Parisi et al. (2005). This index is based on the principle that the higher the soil quality, the greater the number of microarthropod groups well-adapted to the edaphic environment. Unlike traditional abundance-based metrics, the QBS-ar utilizes a qualitative approach centered on the Eco-Morphological Index (EMI). Each taxonomic group (usually at the Class or Order level) extracted from the soil samples is assigned an EMI score ranging from 1 to 20, reflecting its degree of adaptation to the soil matrix.

The assignment of EMI scores is based on the presence of specific morphological specializations, including:

(i) Pigmentation and vision: Reduction or total loss of body pigmentation and visual apparatus (ocelli or eyes).
(ii) Appendages: Reduction in the length of antennae and legs, and the loss or modification of jumping (e.g., the furcula in Collembola) or flying organs.
(iii) Body form: Development of streamlined, tiny, or blind body forms adapted to movement within the interstitial pore space.

Groups showing the highest degree of specialization (eu-edaphic forms, such as Protura, Diplura, or certain families of Coleoptera and Collembola) are assigned a maximum score of 20, while epigeic groups with no specific soil adaptations receive a score of 1. The final QBS-ar value is the sum of the highest EMI scores recorded for each taxonomic group present in the sample.

2.2. Data collection and inclusion criteria

The literature search was performed across Scopus and Google Scholar using the specific keywords “QBS-ar” and Soil Biological Quality index. To minimize subjective selection bias and provide a transparent snapshot of the index's global application, an inclusive collection strategy was adopted: all identified peer-reviewed articles and technical reports published between 2002 and 2025 were retained for analysis (data sources can be find in Supplemental materials). When available, mean QBS-ar values were extracted from the original articles; otherwise, median values were recorded. In cases where numerical data were not explicitly provided in the text or tables, values were digitally extracted from published figures using PlotDigitizer (version 3)(“PlotDigitizer,” 2023). Observations reporting QBS-ar values, land use type, sampling year, and geographic region of the samples (Country) were retained. Where available, information on soil management practices, vegetation cover, and disturbance types was also extracted. A total of 826 observations were included (the list of observations and the corresponding references are reported in Supplemental materials).

Each observation was classified into one of the following land use categories, adapted from Corine Land Cover and IPCC guidelines: F: Forests (broadleaf, coniferous, mixed), GM: Grasslands and Meadows (including steppes and shrublands), A: Agricultural lands (arable, pasture, legumes, root crops), U: Urban and semi-urban areas, B: Barren and Non-Vegetated Land, VO: Vineyards and Orchards (including olive groves), WR: Wetlands and Riparian Zones.

Where applicable, the level of disturbance (e.g. post-fire, post-mining, contamination, intensive management) was recorded as categorical metadata. Within the agricultural subset, we categorized practices into four main types: Conventional, Organic, No-tillage, Conservation agriculture. Where specified in the original studies, disturbances associated with each land use type were also recorded. These included categories such as contamination (e.g., heavy metals, pesticides), post-fire regeneration, post-mining areas, post-storm damage, bioturbation (e.g., ant nests), extreme environments, and management regimes (e.g., managed forests).

Entries without clear information, land use, management practices, or disturbance were marked as "unspecified" and excluded from relevant comparisons within the category; instead, they were retained for broader geographical and global-mean analyses. No studies were

excluded based on perceived data quality or lack of methodological detail. This approach ensures that the resulting reference framework reflects the entirety of the published 'methodological landscape' rather than a curated subset.

2.3. Statistical analyses

All statistical analyses were conducted in R (version 4.4.0)(R Core Team, 2025).

Basic descriptive statistics (mean, median, standard deviation, range) were computed for QBS-ar across the full dataset and by land use type, vegetation cover, and management class. Given the non-normal distribution of the QBS-ar scores (Shapiro-Wilk test, $W = 0.81$, $p < 0.001$), non-parametric methods were employed throughout the study. For each land-use category, we calculated the median and the 95% Confidence Intervals (CIs) using a bootstrapping procedure ($R = 5000$ iterations). This approach allows for a more reliable quantification of uncertainty compared to standard error, especially in categories with high variability.

To test for differences in QBS-ar scores among land use categories and management systems, we employed Pairwise Wilcoxon rank-sum tests with Holm correction for multiple comparisons.

To evaluate the ecological magnitude of the differences beyond simple statistical significance, we calculated the Effect Size (r) for all pairwise comparisons. The r value was derived from the Z statistic ($r = |Z/\sqrt{N}|$) and interpreted following Cohen's benchmarks (Cohen, 2013): small ($r < 0.3$), moderate ($0.3 \leq r < 0.5$), and large ($r \geq 0.5$).Subsets of the data (forest, urban, grassland systems) were used to analyze the impact of different types of anthropogenic or natural disturbances on QBS-ar values using the same non-parametric methods described above. Plots and maps were generated using the *ggplot2* (Husson et al., 2020) and *sf* (Pebesma et al., 2025) packages in R.

2.4. QBS-ar explorer development

QBS-ar explorer, an interactive application implemented in R using the packages *shiny* (Chang et al., 2015), *ggplot2* (Husson et al., 2020), *dplyr* (Wickham et al., 2021), and *DT* (Husson et al., 2020), was developed to contextualize individual soil QBS-ar values within the global reference dataset available in the literature. Users can input their QBS-ar value along with site descriptors, including country, land use, subcategory, management, and disturbance level.

The reference dataset contains published QBS-ar values and associated metadata. Data were checked for consistency, ensuring numeric values for QBS-ar and standardized categorical descriptors, with missing values excluded. The Shiny app dynamically filters the dataset based on user-selected descriptors, displays QBS-ar distributions via boxplots, and overlays the user's value, classifying it into quartiles with a relative assessment ("Poor", "Fair", "Good", "Excellent"). The quartiles and rankings reflect the user's position relative to published data and should not be interpreted as absolute soil quality measures.

QBS-ar explorer is accessible online at https://www.soilarthropo-lab.unipr.it/index.php/qbs-ar-explorer/.

3. Results

The dataset comprises 826 observations collected between 2002 and 2025, encompassing a broad range of land uses and geographic regions.

Most data were collected between 2013 and 2022, and sampling sites are distributed across multiple countries, predominantly in Europe, South America, and parts of Asia (Fig. 1).

Spatial mapping of mean QBS-ar scores across sampled countries reveals geographic variability in data recorded for soil biological quality (Fig. 2). Differences between country ($p < 0.05$) persist even excluding studies focused on soil disturbances (in some countries only soil disturbances were investigated, thus resulting in lower QBS-ar not necessarily linked to the country itself).

The dataset includes multiple land use categories: F, A, VO, GM, B, W*R*, and U. Lower values were observed in U, including sites in England, Czech Republic, and Poland, due to the focus of these studies on soil affected by different disturbances (Table S1).

In total, the dataset encompassed a wide range of contexts (Fig. 3,): for instance, Italy contributed data for all land use categories, with particularly high representation of F ($n = 254$), GM ($n = 84$), and A ($n = 125$). Other countries with diverse land use representation included Hungary, India, and Spain.

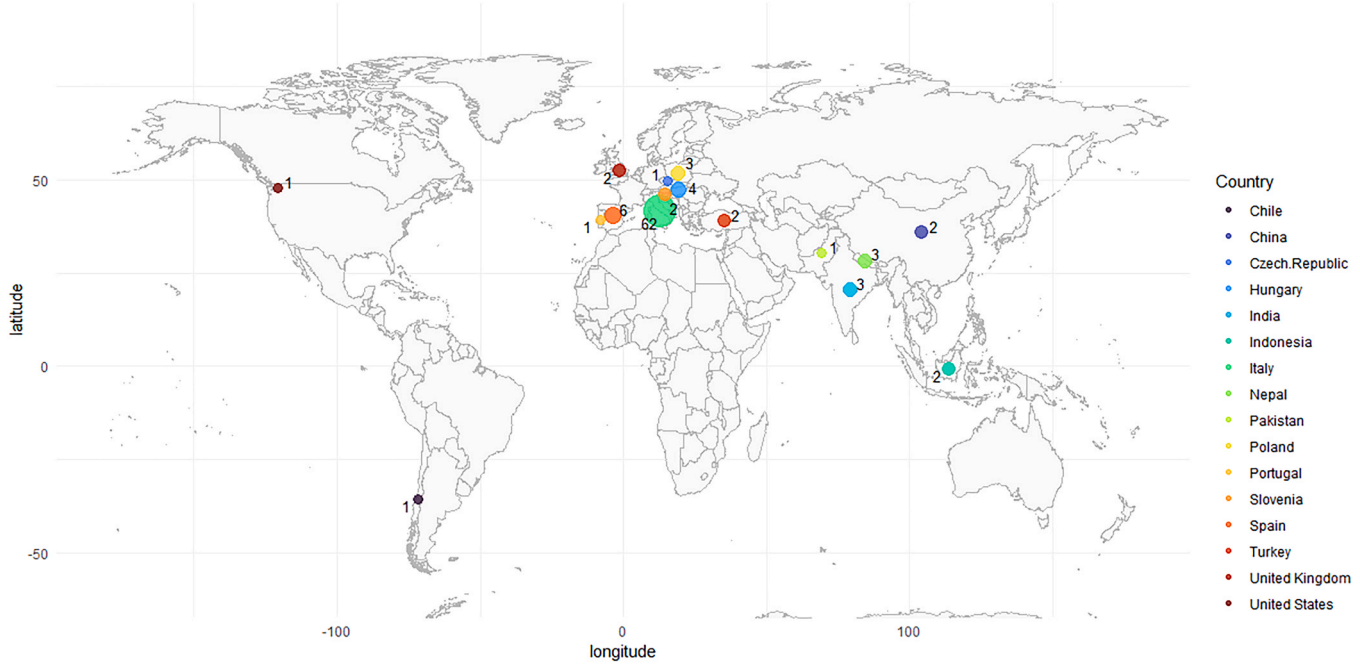


Fig. 1. Geographical distribution of the countries for which QBS-ar data have been recorded and the number of articles reporting studies in those countries. Dot size is proportional to the number of articles.

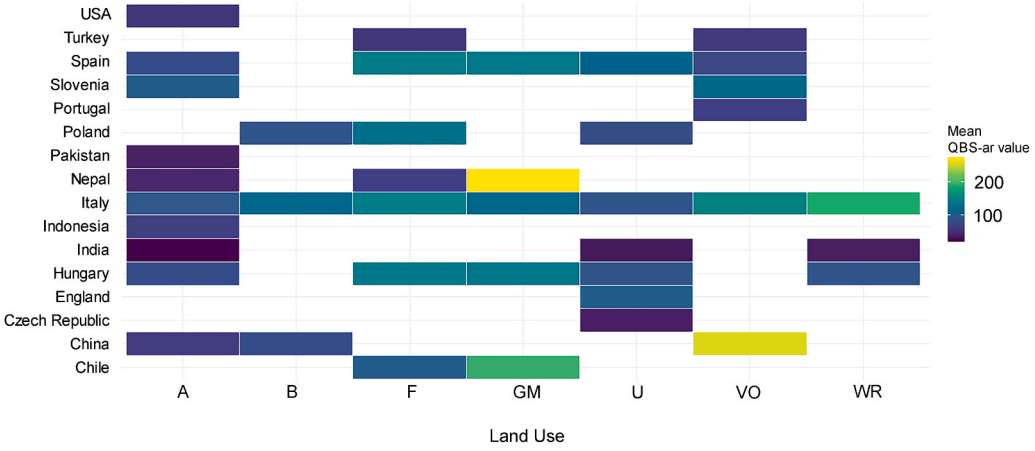


Fig. 2. Spatial mapping of mean QBS-ar scores across sampled countries. F: Forests (broadleaf, coniferous, mixed), GM: Grasslands and Meadows (including steppes and shrublands), A: Agricultural lands (arable, pasture, legumes, root crops), U: Urban and semi-urban areas, B: Barren and Non-Vegetated Land, VO: Vineyards and Orchards (including olive groves), WR: Wetlands and Riparian Zones.

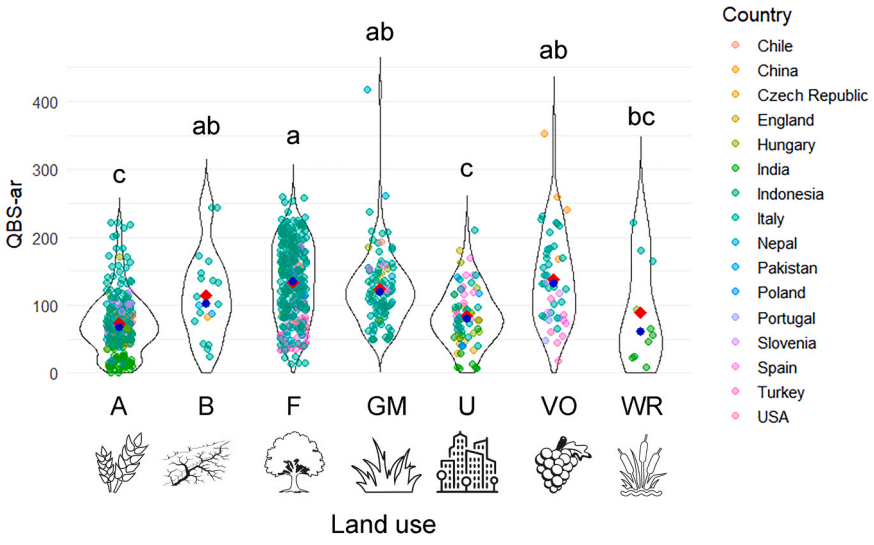


Fig. 3. Distribution of QBS-ar values across different land-use categories. Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each land-use type, respectively. F: Forests (broadleaf, coniferous, mixed), GM: Grasslands and Meadows (including steppes and shrublands), A: Agricultural lands (arable, pasture, legumes, root crops), U: Urban and semi-urban areas, B: Barren and Non-Vegetated Land, VO: Vineyards and Orchards (including olive groves), WR: Wetlands and Riparian Zones. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

In South America, Chilean forested sites displayed moderate to high QBS-ar values, whereas in Asia, particularly India and Pakistan, values were generally lower and more variable. The greatest spatial heterogeneity in QBS-ar scores was observed in Italy, where most of the studies were conducted.

QBS-ar scores range from 0 to 417.0, with a median of approximately 100 and a mean of 109.86 (Table S2). The highest mean QBS-ar values were recorded in vineyards and orchards (mean = 138), forests (mean = 133), and grasslands and meadows (mean = 123).

Pairwise comparisons indicated significant differences between agricultural lands and all other land use categories ($p < 0.001$, all) except wetlands and urban zones (Table 2). Urban areas differed significantly from forests, barren soils, grasslands and vineyards, too ($p < 0.001$). Wetlands and ripariam zones only differed from forests ($p < 0.01$).

Table 2
Significant pairwise comparisons of QBS-ar by Land use including the Effect size (r) and the magnitude of the difference. (F: Forests (broadleaf, coniferous, mixed), GM: Grasslands and Meadows (including steppes and shrublands), A: Agricultural lands (arable, pasture, legumes, root crops), U: Urban and semi-urban areas, B: Barren and Non-Vegetated Land, VO: Vineyards and Orchards (including olive groves), WR: Wetlands and Riparian Zones).

Land use comparisons	Effect size (r)	Magnitude
A-F	0.707	Large
A-B	0.635	Large
A-VO	0.627	Large
A-GM	0.613	Large
U-B	0.457	Moderate
U-F	0.448	Moderate
U-VO	0.443	Moderate
U-GM	0.421	Moderate
F-WR	0.231	Small

3.1. Agricultural land

The agricultural subset includes 240 observations collected between 2002 and 2025, primarily between 2010 and 2020. Most sites are

classified as arable land (n = 97), followed by pasture (n = 16), leguminous crops (n = 5), and root and tuber crops (n = 2) (Fig. 4a, Table S3a). QBS-ar scores in agricultural systems ranged from 0.1 to 222.0, with a median of 67.3 and a mean of 72.63. Leguminous and root vegetable crops exhibited higher mean QBS-ar values (124 and 95.3, respectively) compared to arable and pastureland. No significant differences were observed within agricultural systems.

Agricultural management types were recorded as conventional farming (n = 55), no-tillage (n = 31), organic farming (n = 23), and conservation agriculture (n = 13) (Fig. 4b, Table S3b), with management data missing for 118 entries. Organic systems exhibited the highest mean QBS-ar (109), which was significantly greater than both conventional (mean = 73.6) and no-tillage (mean = 74.0) systems ($p < 0.01$, both) and exhibited a moderate magnitude of effect (r = 0.396 and 0.434, respectively). While conservative agriculture outperformed conventional and no-tillage systems ($p < 0.05$, both), the magnitude of the difference compared to conventional farming remained small (r = 0.268), being moderate when compared to no-tillage (r = 0.351). The bootstrapped 95% CIs confirm that conventional farming results in the most predictable (lowest variability) biological quality scores, whereas organic systems show a broader range of high-quality biological status (CI: 90.65–117.00).

3.2. Forested land

The forest dataset consists of 315 observations collected between 2005 and 2025, with data concentrated between 2014 and 2022 (median year = 2019). All sites are classified under the forest land use category, with subcategories including broadleaf, coniferous, and mixed forests (Fig. 5a, Table 4a). QBS-ar values ranged from 13.3 to 259.0, with a median of 134.9 and a mean of 133.0. Among forest types, broadleaf forests had the highest mean QBS-ar values (140), followed by coniferous (122; $p < 0.05$) and mixed forests (92.0; $p < 0.001$). While certain comparisons are statistically significant, the small effect sizes

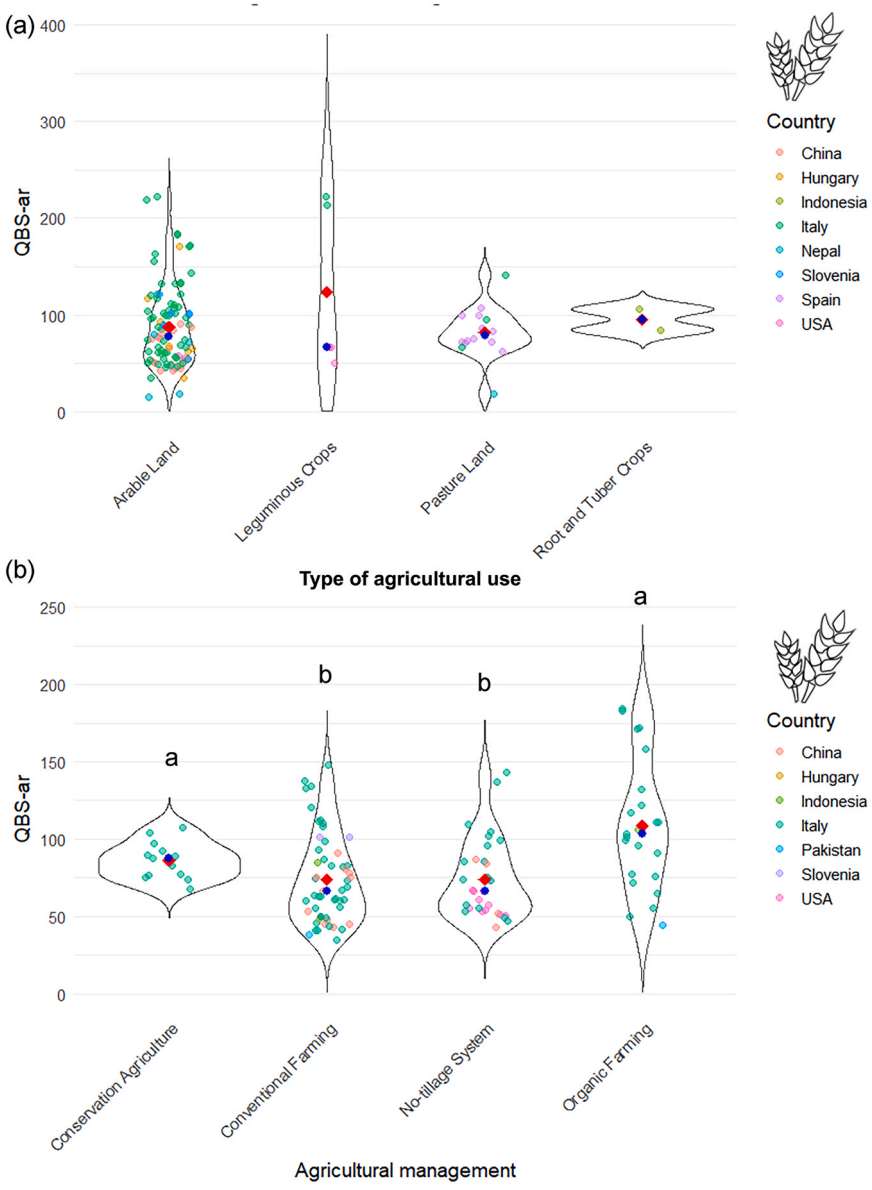


Fig. 4. Distribution of QBS-ar values across different A: (a) types of agricultural use and (b) managements. Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each A subcategory/management, respectively. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

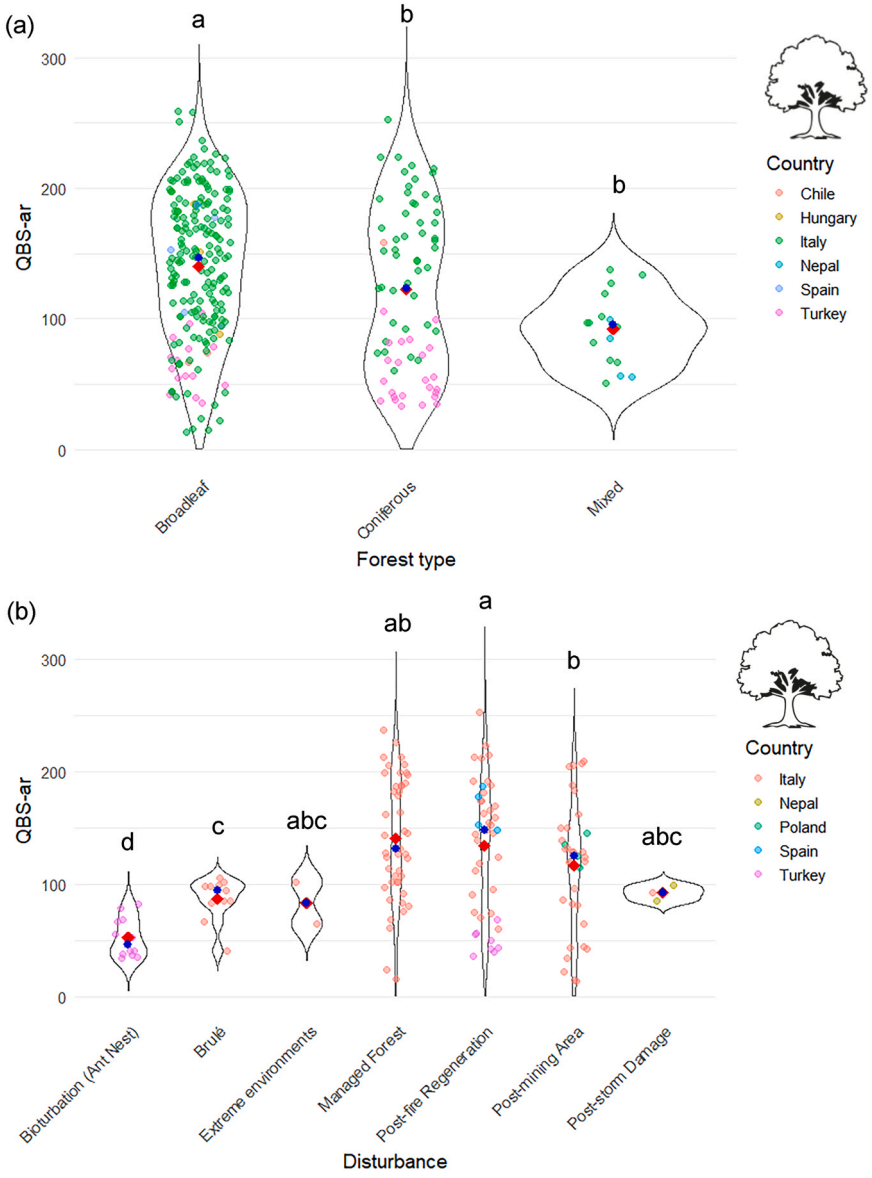


Fig. 5. Distribution of QBS-ar values across different F: (a) types and (b). Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each F type/disturbance, respectively. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

($r < 0.3$) suggest that the variation within these subcategories is less impactful than the broader land-use gradients previously identified.

Data related to disturbed soils were available for 212 records, including post-mining (n = 57), managed forests (n = 45), and post-fire regeneration (n = 44) (Fig. 5b, Table 4b). QBS-ar means varied across disturbance types, stressors like bioturbation and brûlé represent the most significant biological deviations within forest stands, often showing large effect sizes when compared to managed or post-fire areas (Table 3).

3.3. Grasslands and meadows

The grassland subset consists of 98 observations collected between 2002 and 2025, mostly within the last decade (median year = 2020). Sites were classified as grasslands (n = 61), shrubland and steppe (n = 21), and meadows (n = 16) (Table S5a). QBS-ar scores ranged from 48.9 to 417.0, with a mean of 123.3 and a median of 119.4 (Fig. 6). Mean QBS-ar values for grasslands and shrubland/steppe were 131, while meadows exhibited a significantly lower mean value of 83.0

Table 3
Significant pairwise comparisons of QBS-ar for forest disturbances, including the Effect size (r) and the magnitude of the difference.

Group 1	Group 2	p-value	Effect Size (r)	Magnitude
Post-fire	Brûlé	< 0.01	0.742	Large
Bioturbation	Post-fire	< 0.01	0.728	Large
Bioturbation	Brûlé	< 0.001	0.719	Large
Bioturbation	Post-storm	< 0.01	0.671	Large
Managed	Bioturbation	< 0.001	0.614	Large
Extreme environments	Bioturbation	< 0.001	0.549	Large
Bioturbation	Post-mining	< 0.001	0.495	Moderate
Managed	Brûlé	< 0.001	0.440	Moderate
Post-mining	Post-fire	< 0.05	0.319	Moderate
Post-mining	Brûlé	< 0.05	0.302	Moderate

($p < 0.001$ compared to both), with moderate and large effect size respectively ($r = 0.432$ and $r = 0.514$).

Disturbance data were available for 18 observations, including post-mining (n = 10, mean: 110.36), post-fire regeneration (n = 6, mean:

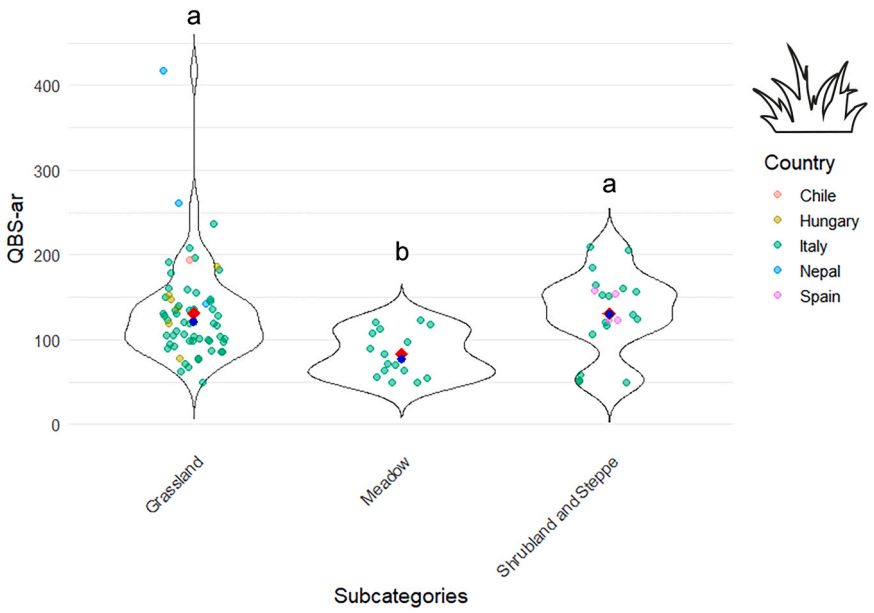


Fig. 6. Distribution of QBS-ar values across different GM subcategories. Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each GM subcategories, respectively. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

105.93), post-storm damage (n = 1, QBS-ar: 101.5), and contaminated sites (n = 1, QBS-ar: 106) (Table S5b). Post-mining showed the highest variability, with values from 49.08 to 205.5. Within grasslands, post-fire effects resulted in a moderate reduction in biological quality compared to post-mining sites ($p < 0.05$; $r = 0.490$). The undisturbed grassland baseline (N = 74) provides a high-precision reference point (CI: 99.03–134.00), against which the high variability of post-mining sites (CI: 52.29–185.32) can be interpreted as a sign of heterogeneous recovery.

3.4. Urban and semi-urban areas

The urban subset includes 69 observations collected between 2008 and 2025, primarily between 2013 and 2021 (median year = 2016) (Fig. 7). QBS-ar values ranged from 6.9 to 210.8, with a mean of 84.5 and a median of 80.0. Disturbance data were available for 22 records, with the most frequent disturbances being contaminated sites (n = 8), agrochemical and heavy metal pollution (n = 5), post-mining areas (n = 5), and former military sites (n = 4)(Table S6). Within urban disturbance types, former military airports and sites contaminated with pesticides or heavy metals showed the lowest mean QBS-ar values (38.2 and 9.1, respectively). The broad confidence interval for post-mining

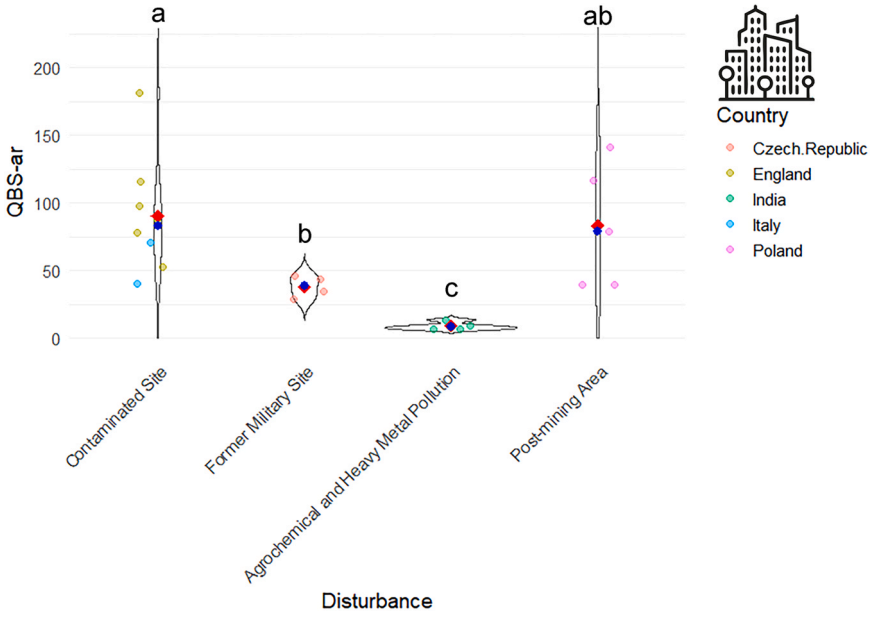


Fig. 7. Distribution of QBS-ar values across different U disturbances. Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each U disturbance, respectively. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

sites (CI: 40.00–141.00, Table S6) highlights a high degree of heterogeneity in biological recovery. The comparison between agrochemical and heavy metal pollution and all other urban disturbances reveals a large effect size ($r > 0.8$ and $p < 0.01$, all), while soils associated with former military airports exhibited a large magnitude of reduction compared to general contaminated sites ($r = 0.686$ and $p < 0.01$)

3.5. Vineyards and orchards

The Mediterranean vineyards and orchards subset comprises 47 observations collected from 2006 to 2025 across multiple countries. Land use categories include vineyards ($n = 24$), orchards ($n = 16$), and olive groves ($n = 5$) (Table S7), with two observations lacking classification. QBS-ar values range from 17.7 to 352, with a median of 131 (Fig. 8). Mean QBS-ar scores were higher in olive groves and orchards (both mean = 177) compared to vineyards (mean = 98.5), with the difference being statistically significant for both comparisons and with a large effect size ($p \leq 0.001$, $r > 0.5$).

4. Discussion

4.1. Comparative performance of the QBS-ar index

In the broader landscape of soil health monitoring, QBS-ar occupies a unique niche between high-resolution taxonomic indices and coarse functional metrics. To describe soil invertebrate communities, ecologists commonly rely on diversity indices; however, these metrics do not incorporate the ecological roles of taxa and therefore have limited effectiveness in evaluating how environmental factors, particularly disturbance, affect soil health (Santorufo et al., 2012). While QBS-ar provides a unique phenotypic signal of soil health, its integration into multi-proxy frameworks alongside molecular tools—such as eDNA metabarcoding—and biochemical indicators (e.g., enzyme activities or PLFA) represents the current frontier of soil monitoring. When compared to eDNA metabarcoding, while the latter offers superior taxonomic depth, QBS-ar remains more accessible for routine monitoring and directly reflects the functional adaptation to the edaphic environment—a physical dimension often missing from genetic data. Furthermore, compared to other faunal indices like the Nematode Maturity Index (MI), QBS-ar shows higher sensitivity to physical soil structure changes and compaction, making it a critical biological pillar in integrated assessment frameworks that combine chemical and physical parameters. This paper compiles and analyses QBS-ar values reported in the literature with the aim of updating current knowledge regarding the reference values of the index across different land-use types and its global geographical extent of application. The objective is to highlight both the versatility of QBS-ar in assessing soil health and soil biological quality across different land-use types and geographical contexts, and the variability in values observed. Because the methodology involves the inclusion of all published data without selective filtering, the results inherently reflect existing reporting biases within the scientific community, such as the high density of studies in specific European regions and the frequent omission of detailed EMI documentation. By presenting the data in this raw, inclusive format, the paper provides a more honest assessment of the current noise in global QBS-ar research and highlights the specific areas where standardization is most urgently needed.

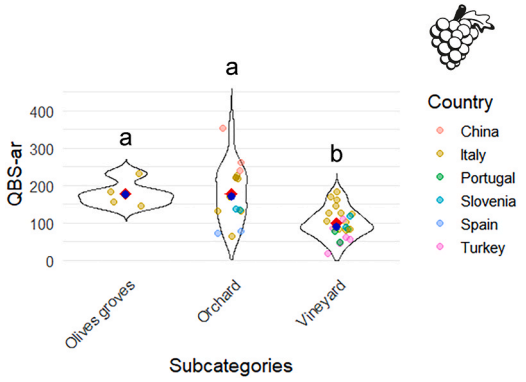


Fig. 8. Distribution of QBS-ar values across different VO subcategories. Violin plots display the density of QBS-ar scores, with individual observations coloured by country. Red diamonds and blue dots represent mean and median QBS-ar values for each VO subcategories, respectively. Different letters placed above violins indicate that the groups are significantly different from each other ($p < 0.05$), groups sharing the same letter are not significantly different.

4.2. Global spatial distribution and land-use variability

The analysis reveals substantial spatial and land-use-related variability in soil biological quality as measured by the QBS-ar index. However, differences between countries and land uses are often difficult to interpret, as some datasets only include soils that experienced some form of disturbance. Nonetheless, an intrinsic geographical difference was already observed in Menta et al. (2018) and is assumed to be linked not only to climatic conditions but also to differences in soil management practices. In fact, countries not only vary in terms of the technologies applied but also in the purpose of land use, often associated with their primary production systems.

It is well established that, even within agricultural soils, differences between crop types can be substantial (Remelli et al., 2025). For this reason, assessing fluctuations in soil biological quality on a global scale is essential to understand how far a given soil condition deviates from a potential "standard." In this context, it is encouraging to note that while (Menta et al., 2018) reported QBS-ar data from only seven countries, the number of countries applying the index has now doubled to 16, distributed across the globe, still maintaining an overall mean very similar to that observed 7 years ago (110, now, versus 94).Forested ecosystems consistently exhibited the highest mean QBS-ar values, particularly broadleaf forests. These systems are known to support well-structured and stable microarthropod communities, largely due to the continuous input of organic matter and abundant litter (Blasi et al., 2013; Fusco et al., 2023a; Rodríguez-Pajares et al., 2025). These findings underscore the ecological importance of tree cover and structural complexity in sustaining diverse soil arthropod communities.

Conversely, urban environments and intensively managed agricultural systems showed significantly lower QBS-ar values, reflecting the negative impact of anthropogenic disturbance on soil fauna. Grassland systems, including alpine grasslands and pasture meadows, often produced highly variable but generally lower QBS-ar scores than forests and rarely exceeded a value of 200 (Fusco et al., 2023b; Gardi et al., 2002; Menta et al., 2011, 2008; Rüdisser et al., 2015). However, when all data in the present study are considered, no significant differences between forests and grassland sites were observed. This result shows that both environments are important reservoirs of biodiversity.

Geographic patterns further reinforce the link between land use intensity and soil quality. Southern European regions, especially Italy, Spain, and Portugal, demonstrated higher QBS-ar values, particularly in forests and perennial cropping systems such as vineyards and orchards. In contrast, lower values were associated with urban environments in Central and Eastern Europe and with agricultural areas in South Asia, where intensive practices and legacy disturbances likely suppress soil biodiversity (Liira -Tsipe and Zobel, 2008).

4.3. Impact of management and disturbance legacy

In agro-ecosystems, management practices significantly affect various aspects of soil quality, including biodiversity, structural stability, nutrient availability, and resilience to disturbance or stress (Urruty et al., 2016). This metanalysis confirms that agricultural practices exert

a strong influence on soil biological quality. Specifically, organic farming systems exhibited significantly higher QBS-ar values compared to both conventional and no-tillage systems. This suggests that the reduction of chemical inputs and the enhancement of soil organic matter under organic management promote more diverse and abundant soil arthropod communities. In effect, soil arthropods are known to be highly sensitive to changes in agricultural practices (Crossley et al., 1992), and previous studies have shown that organically managed fields tend to harbor a higher abundance and diversity of arthropods than conventionally managed systems (Berry et al., 1996; Hole et al., 2005; Mantoni et al., 2021; Pimentel et al., 2005; Reddersen, 1997). Similarly, leguminous and root crops were associated with elevated QBS-ar scores, likely due to their positive effects on soil structure and nitrogen content. These results are consistent with those reported by (Fiorini et al., 2022), who observed that leguminous-based mulching enhances soil fauna. Overall, these findings support the idea that diversified, and ecologically sensitive farming systems can help mitigate biodiversity loss in agricultural landscapes.

Grasslands and meadows also exhibited relatively high QBS-ar values, particularly in semi-natural shrublands and steppes, whereas intensively managed meadows showed lower scores. This supports the hypothesis that plant community permanence and reduced disturbance levels enhance soil faunal diversity. In Menta et al. (2011) grassland sites show complex edaphic communities both taxonomically and functionally, with predator and phytophagous groups in addition to fungi and debris feeders. Moreover, the high variability observed within grasslands and shrublands may be attributed to the role of litter quality as a primary driver of changes in soil fauna and flora populations (Kooch and Noghre, 2020).

Notably, despite the presence of disturbances such as fire, mining, and bioturbation, many grassland and forest sites retained high QBS-ar values. This suggests a degree of resilience and potential for recovery in ecosystems that have undergone less intensive modification (e.g., Fusco et al., 2023a). However, certain types of disturbance—particularly industrial contamination and historical military activities—were associated with the lowest QBS-ar values in urban contexts, highlighting the long-term degradation linked to persistent pollutants. Indeed, Tóth et al. (2023) emphasized that even low to moderate levels of pollution can negatively affect edaphic fauna, indicating biological degradation of soils even below established pollution thresholds.

These findings underscore the importance of considering legacy effects when evaluating soil biological quality.

4.4. Methodological challenges and the future of digital ecology

Finally, the data presented here—especially those at the extremes of the QBS-ar range—should be interpreted with caution. Most studies do not report the specific EMI (biological form) assignments used in calculating the index, making it difficult to verify the accuracy and consistency of the methodology. Consequently, some of the extremely high or low values raise concerns about methodological reliability. This highlights the urgent need for future research to clearly document the EMI classification criteria employed and to critically evaluate the appropriateness of QBS-ar application. Such transparency is essential to ensure the comparability and robustness of QBS-ar as a tool for soil quality assessment.

Additionally, tools such as *QBS-ar explorer* provide a framework for interpreting individual QBS-ar values in the context of a global reference dataset. The quartiles and ranking positions offered by the tool allow for a relative assessment of soil biological quality, indicating whether a sample falls within low, medium, or high ranges compared to published data. It is important to note that these relative positions should not be taken as absolute measures of soil quality, but rather as a comparative guide to contextualize results within the available literature. This approach facilitates informed interpretation, particularly when evaluating values at the extremes of the QBS-ar distribution.

As soil health monitoring moves toward global integration, the QBS-ar index must evolve from a localized metric into a standardized component of multi-proxy assessment frameworks.

The future development of the field should prioritize three key pillars:

1. Methodological harmonization: To mitigate the "observer effect" and the heterogeneity identified in this meta-analysis, the development of a digitalized, open-access EMI catalog is essential. This would provide a consensus-based, image-led key for morphotype assignment, ensuring that biological quality scores are numerically and ecologically comparable across continents.
2. Integration into multi-proxy Indices: QBS-ar should be systematically coupled with physical and chemical indicators (e.g., bulk density, TOC, and nutrient cycling) to form Integrated soil quality indices. This holistic approach would better elucidate the feedback loops between faunal activity and ecosystem services.
3. Landscape-scale monitoring: leveraging the data synthesized here, future research should focus on developing predictive models that use QBS-ar benchmarks to assess the restoration success of degraded lands or the resilience of agroecosystems to climate change-induced disturbances.

The recent trajectory of the field is characterized by a shift toward digital ecology. Key advances include the development of interactive global databases—such as the QBS-ar explorer introduced here—and the emerging use of machine learning for automated morphotype recognition. These tools are transforming the index from a manual, expert-dependent metric into a scalable, data-driven framework capable of supporting landscape-scale restoration monitoring and precision agriculture.

5. Conclusions

Overall, this synthesis demonstrates that QBS-ar is a sensitive and informative indicator of soil ecological status across a wide range of environmental contexts. Its responsiveness to land use, management, and disturbance makes it a valuable tool for monitoring soil biodiversity and informing sustainable land-use planning. The growing number of countries applying the index—from 7 to 16—confirms the increasing international relevance of QBS-ar and underscores its potential for global comparisons. However, this expansion also reveals the challenges of interpreting variability across regions and land uses, especially when methodological details, such as EMI classification, are inconsistently reported. An important aspect to consider in this meta-analysis is that certain land-use categories are supported by extensive datasets, whereas others are represented by a limited number of observations and are further restricted to only a few geographical regions. This data heterogeneity allows for robust inferences regarding land-use ranges only where data density is sufficiently high, while in data-poor categories additional studies and further applications of the index are required to strengthen the reliability of the assessments.

Further efforts to standardize metadata collection—particularly concerning management practices, disturbance histories, and methodological choices—would greatly enhance the comparability and interpretability of QBS-ar studies.

Moreover, the inclusion of reference or benchmark sites for different soil types and land uses would help contextualize observed values and identify deviations from ecologically sustainable conditions. As anthropogenic pressures on soils intensify, the use of robust and scalable biological indicators like QBS-ar becomes increasingly essential—not only to detect degradation but also to guide restoration and conservation efforts.

CRediT authorship contribution statement

Cristina Menta: Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Conceptualization. **Sara Remelli:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, 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.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2026.110375.

Data availability

Data will be made available on request.

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