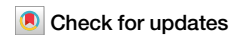


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Soil health in Latin America and the Caribbean



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Socio-economic progress relies on critical soil ecosystem services, yet Latin American and Caribbean soils face considerable pressures. Here we assess soil health across the region using remote sensing data processed with cloud-based machine learning to create high-resolution maps (90 m) of a soil health index. This index integrates weighted physical, chemical, and biological indicators, such as total porosity, plant-available water, and carbon stock. Based on five soil functions, which involve water and nutrient fluxes, carbon sequestration, and supporting plant growth, we found that 38% of soils are classified as unhealthy, 28% as moderate, and 34% as healthy. Unhealthy soils dominate drylands and savannas with frequent surface exposure, while humid equatorial zones exhibit healthier conditions. Notably, the Amazon basin registers medium-low soil health, underscoring the urgent need for conservation. Our findings offer a robust framework for soil protection policies and restoration strategies to enhance sustainability and ecosystem resilience.

Traditional soil evaluation has greatly enhanced our understanding of soil properties, including pedology, pedometrics, and related disciplines. However, the exponential growth of soil health (SH) brings new perspectives that emphasize a holistic assessment of physical, chemical, and biological indicators. Soil health is considered “the frontier of soil science”¹. This comprehensive approach recognizes the intricate interplay of these factors, directly influencing the soil’s functioning and the provision of critical ecosystem services. Therefore, SH can be defined as the continued capacity of soil to function as a vital living ecosystem, sustaining plants, animals, and humans while connecting agricultural and soil science with policy, stakeholder needs, and sustainable supply chain management². This multidimensional concept integrates physical, chemical, and biological soil properties, reflecting its ability to support agricultural productivity, regulate water and nutrient cycles, sequester carbon, resist erosion, and promote biodiversity.

Healthy soils are associated with higher primary productivity³ and resilience to climate change⁴. Thus, they play a pivotal role in reconciling food security, climate change mitigation and adaptation, and human health⁵. These issues are particularly urgent in Latin America and the Caribbean (LAC)⁶, where reverse soil degradation is a challenge due to unsustainable land use and management, including high pressure of deforestation⁷ and forest disturbance (e.g., logging and fires), loss of biodiversity⁸, soil erosion⁹, and high vulnerability to climate change¹⁰. Consequently, the SH approach guides informed land use and management decisions, ensuring the preservation of fragile soil resources for future generations¹¹. Maintaining healthy soils is imperative for attaining the

United Nations Sustainable Development Goals in the forthcoming decades¹² and keeping planetary boundaries within a safety zone for humanity^{13,14}.

The SH assessment involves monitoring primary and crucial soil functions for ecosystem health and sustainability¹⁵. These functions include vital processes such as nutrient cycling, water regulation, biodiversity support, carbon sequestration, physical support to plant growth, and cultural services^{2,16,17}. Soil attributes and environmental processes are closely related to these soil functions^{12,16}. For instance, nutrient cycling, including elements like nitrogen and phosphorus, relies on the availability of essential elements and specific soil conditions^{18,19}. Similarly, soil porosity, infiltration rates, and water-holding capacity directly impact water flux regulation^{20,21}.

However, spatial assessment of SH faces additional challenges due to the complex interactions between soil attributes and their spatial patterns²². Therefore, more comprehensive methods for broad spatial assessment of soil health (soil conditions) need to be developed. Even when soil datasets are available on a global scale^{23,24}, they have gaps due to remote or inaccessible regions, causing generalizations in the assessment of soil nuances across landscapes and climates worldwide^{25–27}. Georeferenced soil data scarcity and incomplete or uneven global distribution limit the SH assessment to traditional site-based methods, restricting them to a local or regional scale. Therefore, digital soil mapping (DSM) enables the spatialization of soil indicators and the SH, offering a solution by integrating various soil datasets to generate continuous maps as valuable input data for globally assessing SH.

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Typically, DSM relies on machine learning algorithms informed by proxies of formation factors, including soil, climate, organisms, topography, parental material, age, and space (the SCORPAN model) derived from remotely sensed data²⁸. Mapping on a large scale requires advanced techniques for processing large datasets, producing accurate soil proxies, and analyzing complex relationships²⁹. Remote sensing and data science offer efficient solutions by addressing many limitations of traditional soil assessment methods³⁰. Consequently, machine learning algorithms, satellite imagery, field observations, terrain attributes, and climatic data enable the prediction of soil properties at various scales^{26,27,31}. The information generated provides a holistic understanding of soil conditions, identifying, for instance, areas at risk of degradation or implementing management zones.

Research and DSM efforts on SH often center on specific regions³² or individual soil attributes^{27,33,34}, leading to gaps in our understanding of integrated SH on a broader scale. Integrating various soil indicators into a comprehensive Soil Health Index (SHI), a single metric that adequately captures the nuances of each environment can be challenging due to the complexity of soil systems^{2,20,35,36}. This metric characterizes the ability of soil to perform primary functions in a given ecosystem for a given period.

Therefore, studies that combine remote sensing, data science and SH expertise are innovative and valuable because they allow SH assessments and mapping on a continental scale, as we propose for LAC. To the best of our knowledge, no other studies have combined such an in-depth understanding of SH with remote sensing and data science on this scale. By leveraging cloud-based machine learning techniques, we efficiently processed large and diverse datasets, achieving a level of integration and scalability that surpasses previous studies^{2,20,35,37}. These studies used diverse methodologies to assign weights to SH indicators and soil functions, integrating researchers' opinions and statistical analysis. By selecting SH indicators from soil attribute maps and integrating them in a weighted model,

we successfully mapped SH across the LAC region at a resolution of 90 meters. The resulting map that indexed the SH enabled a comprehensive assessment from both agricultural production and environmental conservation perspectives. Consequently, combining empirical knowledge with advanced technologies³⁸, this holistic approach substantially addresses the need for SH assessment within the study region and worldwide.

Results and Discussion

Maps of soil health and functions for the LAC

The Soil Health Index (SHI, Fig. 1) map revealed distinct spatial patterns of soil conditions and functions across the LAC region. Unhealthy soils, indicated by reddish colors, were predominantly associated with sandy textures developed under drier climates. Conversely, healthier soils, indicated by greenish colors, tend to exhibit higher content of clay and silt fractions and were linked with wetter conditions in the region. Notably, nearly 90% of SHI data fell within the range of 0.38 to 0.69 values, showing an inverse relationship with latitude. This observed trend on SHI aligns positively with the spatial heterogeneity of aboveground living plant biomass³⁹. In contrast, SHI declined with increasing Earth's surface exposure²⁶. It reveals a strong correlation between soil cover and SH across the LAC, characterized by elevated aboveground biomass and reduced prevalence of bare surfaces, likely attributed to conventional soil management practices⁴⁰. This discussion leads us to the central issue of soil degradation.

Soil functionality to store, regulate fluxes, and maintain the availability of chemical elements (F_I) remained relatively stable across latitudes (Fig. 1). Near the Equator, F_I values were lowest and gradually increased towards the poles. However, other soil functions exhibited response patterns consistent with the latitudinal patterns observed in the SHI, indicating an increase in soil functionality as plant biomass increased and soils became permanently

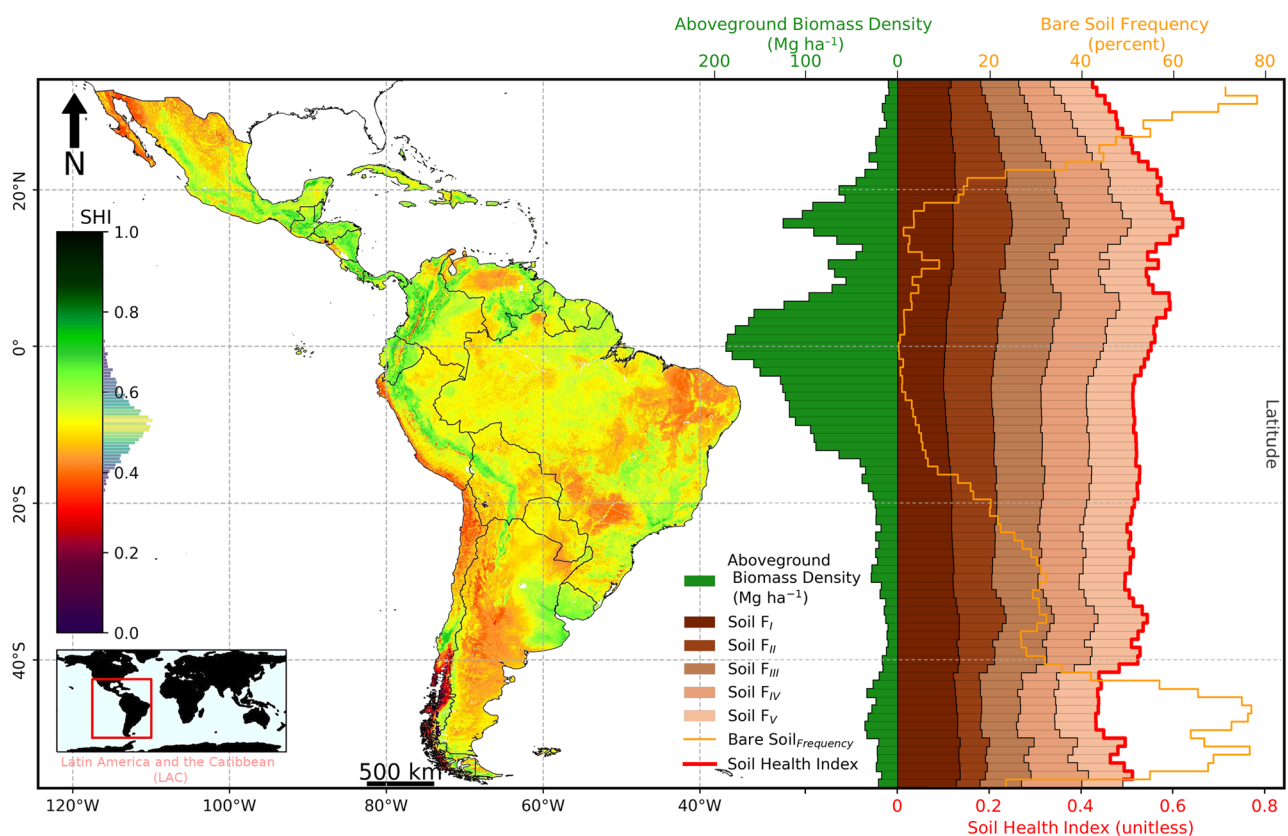


Fig. 1 | Soil health index map for Latin America and the Caribbean. The right side shows latitudinal trends per degree in soil functions, bare soil frequency 26, and aboveground biomass 41 in LAC. Soil Function: FI – Store, regulate fluxes and availability of chemical elements; FII – Regulate water fluxes, storage, and availability

of water; FIII – Sequester soil organic carbon and support soil biodiversity; FIV – Physical support to plant growth; FV – Resist to erosion degradation. For country names, visit <https://raulpoppiel.github.io/rotating-globe/>, and <https://geocis.users.earthengine.app/view/lac-soil-health> for map visualization.

covered. In cool climates of temperate regions, particularly between 56° and 38° south latitudes, soil functionality in regulating water fluxes, storage, and availability (F_{II}) tended to be reduced. However, this reduction in F_{II} gradually inverted, improving as we moved towards subtropical and tropical regions, peaking between 4° south and 15° north latitudes.

The other three functions, including C sequestration and supporting soil biodiversity (F_{III}), physical support to plant growth (F_{IV}), and resistance to erosion degradation (F_V), exhibited similar latitudinal patterns regarding bare soil and vegetal biomass. These functions displayed higher values near the Equator, gradually decreasing towards the poles.

Spatial patterns of soil health in LAC

The spatialization of SHI across the LAC region, previously shown in Fig. 1, varied across percentiles. The observation of the SH spatial patterns enabled identify some of the specificities and complexity of the LAC territory, such as lower SHI in northwestern Brazil most influenced by climate factors (area under high pressure of desertification^{41–43}; intermediate SHI in the Amazon basin signed to vegetation biomass dynamics; middle-low SHI in Central Brazil caused by soil exposure from agricultural practices; higher SHI in the east face of the Andes Mountains related to the landform's heterogeneity. Furthermore, using data legacy, it is possible to sign the SH conditions to pedodiversity, land use and land cover, management practices, and climates, as all these factors drive SH changes².

Latitudinal variation of climate patterns also influenced many phenomena on Earth and has already been demonstrated by several studies using different approaches and data sources to balance physicochemical and biological features³⁹. For instance, the latitudinal patterns impact chemical attributes. In natural terrestrial ecosystems, there is a global trend in which environments shift the limitation from N to P as latitude increases, caused by seasonal precipitation and annual temperature variation¹⁹. It is also true for biological indicators, such as earthworm diversity, in which regional richness in the tropics is likely more important than in the temperate regions³³. Also, regional stability of forest ecosystems and spatial asynchrony decrease as latitude increases³⁹. These and many other studies have demonstrated the impacts and complexity of Earth's system dynamics on the biotic and abiotic environment related to spatial patterns²². Thus, we advocate that latitudinal patterns represented by climate variations are a way to assess the SH suitably in large-scale assessments. However, additional research and effort are required to address the challenges of spatially assessing SH fitted to different regions of the planet. This SH mapping approach facilitated the identification of patterns across the lands, thereby providing a scientific foundation for the formulation of soil conservation policies and programs.

Distribution of soil health across biomes and countries in LAC

The SH assessment conducted by biome and countries provided a comprehensive understanding of socio-economic and environmental challenges in the study region in public policies^{6,15}. We explored SH patterns across biome boundaries, supporting observations within an ecological context. Conversely, analyzing SH by country revealed nuances and variations associated with socio-economic and political factors. To visualize this dual perspective, we employed Sankey's diagram (Fig. 2), which simultaneously illustrated both features by delineating SHI into categorical classes across LAC, varying from class 1 (unhealthier soils) to class 5 (healthier soils). Furthermore, the Supplementary material provides a statistical summary of SHI classes (Table S6), the histogram obtained from the SHI maps (Figure S3), and the classified SHI map (Figure S4). Although the specific limits for each SHI class depend on our database, as SHI scores can vary according to the indicators and indexing strategies used, the rational, statistical approach and meaning behind the classes remain applicable and useful for studies in other ecosystems.

Class 1 gathers the lowest SH levels, where soils present numerous limitations regarding nutrient availability, soil structure, and overall ecosystem functioning. Soils within SH Class 1 cover the driest and hottest LAC regions, such as northwest Mexico, northeast Brazil, south and north Chile

and central Argentina. These areas are marked by deserts or arid climates, where the soils minimally perform their functions. Class 2 reflected moderate soil limitations. Soil conditions may be slightly better than Class 1, but substantial limitations remain in essential soil functions and services provided. Spatially, this class surrounds the patterns of Class 1, predominating in central-south Argentina and central-north Mexico. Class 2 also crosses northwestern Brazil, a savanna region marked by agricultural frontiers under intense pressure on the soils.

Class 3 represented intermediate SHI levels, with ecosystems experiencing a mix of strengths and weaknesses regarding soil functions. While some soil properties may present adequate levels, persistent limitations exist in others. This class made a more noteworthy contribution in the Amazon Rainforest region, where the soils perform moderate functions that need attention in their protection and restoration. Class 3 was the most frequent, with 50% of participation in the forestry biome, and are probably the poor ones.

Class 4 indicates a relatively good SH, where the soil is functioning adequately but still insufficient to achieve full performance. The SHI map shows that class 4 covers flat areas and intermediate to low altitudes at LAC (Figure S4). The equatorial region of LAC, including Guiana, Suriname, far north Brazil and south of the Caribbean, presented good SHI values and represented the soil with middle-high conditions to play their functions. Finally, Class 5 included regions with the highest SH, enhanced soil functioning and provision of ecosystem services. Southwest of Colombia, Ecuador, south Venezuela, Panamá, Guatemala, and Uruguay are countries where Class 5 predominated. The soils are at their maximum capacity to perform their functions in these areas but even need protection to maintain their health in the long term.

For a breakdown, detailed information on SHI class distribution by biome and country can be found in Supplementary Tables S7, S8, respectively. Table Supplementary S7 provides the area quantification of SHI classes across biomes within the LAC region. In the Tropical & Subtropical Moist Broadleaf Forest biome, 42% of the area exhibited high levels of SH (classes 4 and 5). However, most of the SHI values in this biome fell into classes 3, 2, and 1, indicating predominantly low to mid-level healthy soils at high risk of degradation. In biomes under high-pressure anthropogenic pressure, such as the Tropical & Subtropical Grasslands, Savannas, and Shrublands, nearly 90% of the area fell within classes 2, 3, and 4. All biomes had areas within class 1, characterized by the lowest SHI values, with 60% comprising Temperate Grasslands, Savannas, Desert & Xeric Shrublands, and Tropical and Subtropical Grasslands biomes.

The assessment of SHI across countries in the LAC region revealed that diverse factors contributed to the observed patterns and variations, as illustrated on the right side of Fig. 2 and Supplementary Table S8. The distribution of SHI exhibited irregular trends influenced by climate factors and land use and land cover beyond LAC's national borders, highlighting the influence of climate, landscape and anthropogenic activities on soil conditions. Countries (and territories) with a higher proportion of healthier soils (class 5) are predominantly located in Central America and the Caribbean, with notable examples including Belize (71%), Porto Rico (70%), Honduras, and Nicaragua (68%), Costa Rica (65%), Panama (57%) and Guatemala (56%). In addition, countries with more than 50% of class 5 SHI include Ecuador (58%) and Uruguay (51%).

In terms of absolute area, the top five countries with healthier soils are Colombia (316,226 km², 28%), Mexico (282,272 km², 15%), Venezuela (255,979 km², 27%), Brazil (216,006 km², 3%), and Argentina (193,258 km², 7%). However, countries with higher proportions of unhealthier soils (Class 1) include Chile (54%), Argentina (24%), and the Falkland Islands (24%). However, Brazil leads with 918,707 km² (11%), followed by Argentina (656,073 km², 24%), Chile (363,429 km², 54%), Mexico (264,297 km², 15%) and Peru (122,857, 10%). In the intermediate class 3, Brazil had 42% of its territory, accounting for 3,501,724 km², an area almost seven times higher than second-place Peru (512,102 km²). Argentina, Bolivia, and Mexico complete the top five list of SHI in LAC. Supplementary Table S8 provides a detailed description of each country's SH classes (frequency and area). This

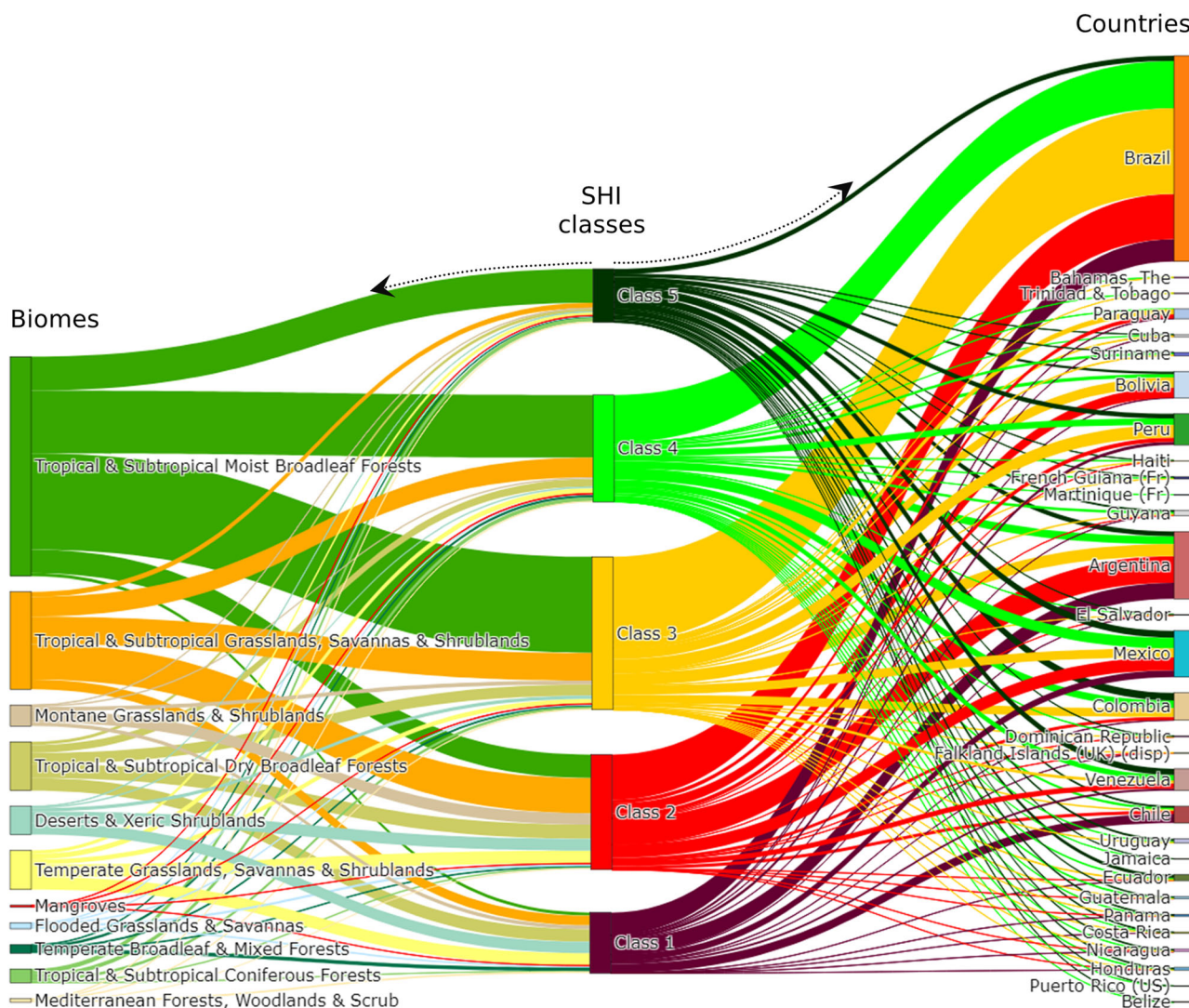


Fig. 2 | Quantifying soil health index (SHI) classes across LAC. Soils become healthier from class 1 (pansy purple) to 5 (dark green). The width of the flows in the Sankey diagram represents the area (km²) distribution of SHI classes (center) among

biomes (left side) and countries (right side) in LAC. Please refer to Tables S1, S2 in the supplementary material for data sources. View the interactive version at <https://raulpoppiel.github.io/lac-shi-sankey/>.

SH information at the national level can be useful for each country to include in its national communications (for example, National Communications for the United Nations Framework Convention on Climate Change - UNFCCC and for the United Nations Convention to Combat Desertification - UNCCD) and guide the elaboration of national programs and policies on soil conservation.

Intrinsic drivers of LAC's soil health

Identifying intrinsic drivers through data modeling for different percentiles of SHI has enriched our understanding of the diverse influences across the SH range. This percentile-based analysis offers valuable insights into soil dynamics and spatial variations, informing targeted interventions for sustainable land management practices in the LAC region³⁰.

SHapley Additive exPlanations (SHAP) values derived from the force plot (Fig. 3) have provided valuable insights into the intrinsic drivers of the SHI in LAC. Soil indicators exhibit varying influences on SHI values across different percentiles. Summarizing the effects of these indicators, we computed the mean SHAP values for each contributor, as depicted in the summary plot (see Supplementary Fig. S5). Predicted values of SHI increased from 0.38 in the 5th percentile to 0.67 in the 95th percentile. Between the 5th and 25th percentiles, the indicators contributed negatively to the SHI, reflecting lower SHI levels. In this example, higher Bulk Density

(BD) has a negative impact on the prediction, while lower values have a positive impact. It suggests that reduced plant-available water (PAW), lower C content, decreased total porosity (TP), lower hydraulic conductivity (K_{sat}), fewer earthworms, and higher bulk density (BD) contribute to decreasing SHI levels. However, at the 50th percentile, there was an equilibrium of influences, with positive and negative contributors coexisting.

Strongly positive contributions to the SHI were observed between the 75th and 95th percentiles for higher values of TP, PAW, nitrogen (N), C and C stock, K_{sat} , cation exchange capacity (CEC), earthworms and lower BD. The strength of each contributor among the percentiles highlights the complex interplay between these indicators and their combined effects on SH in the LAC region.

Identifying additional drivers for SH requires partnerships to strengthen connections between national and local soil and land management programs across the LAC region²⁰. Expanding the scope of SH indicators can reduce the uncertainties in digital maps, leading to a better representation of spatial variability in soil processes and functions².

A comparative analysis of soil health indicators (SHI) reveals substantial differences between high and low SHI values, with critical implications for land management. Biological indicators, particularly carbon (C), are fundamental drivers of soil health assessment¹⁵. Carbon is one of the most widely used indicators due to its role in enhancing soil structure,

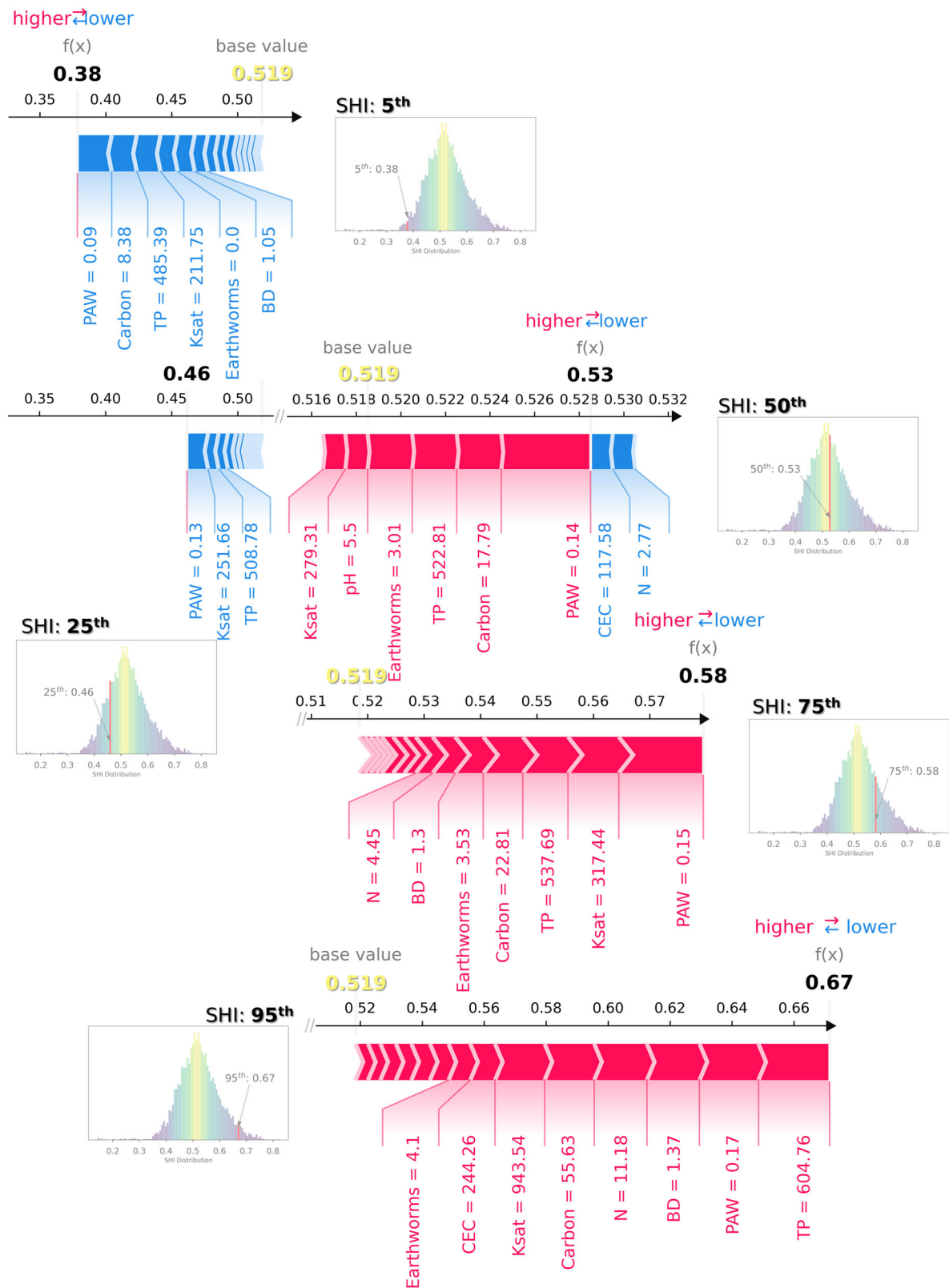


Fig. 3 | Intrinsic drivers of Soil Health Index (SHI) across Latin America and the Caribbean. Force plots illustrate the combined impact of each soil indicator on SHI values, with positive effects depicted in red and negative implications in blue. These indicators ‘compete’ against each other, resulting in deviations of the SHI values (grouped on percentiles) from the expected base SHI value, the mean prediction for

the entire dataset (0.519 in this analysis). By summing the contributions of all the soil indicators and adding the base value, we obtain the model output for each SHI percentile group (0.38, 0.46, 0.53, 0.58, and 0.67 for the respective percentiles 5th, 25th, 50th, 75th, and 95th). Supplementary Fig. S1 provides a summary plot combining feature importance with feature effects.

nutrient retention, and water availability^{2,17,44}. However, data on C dynamics resulting from best management practices remain scarce and unevenly distributed across Latin America and the Caribbean (LAC)⁴⁵. Improving carbon stocks is essential for developing strategies to mitigate climate change, as C content directly supports microbial activity, which drives nutrient cycling and disease suppression. Lower-quality soils can benefit from organic amendments and biodiversity-enhancing practices to strengthen microbial health.

Chemical and physical indicators also play pivotal roles in soil health assessment⁴⁶. High-SHI soils typically maintain balanced levels of macro- and micronutrients to support plant growth, while low-SHI soils often exhibit deficiencies requiring targeted fertilization and amendments. Soil pH is a critical factor; higher-SHI soils generally have optimal pH levels for nutrient uptake, whereas lower-SHI soils may suffer from acidity or alkalinity issues that restrict nutrient availability, necessitating lime or sulfur applications. Soil acidity and toxic aluminum are particularly important indicators in tropical and highly weathered soils⁴⁴. Coordinated efforts to develop high-resolution maps of biological, chemical, physical, and carbon-related indicators are urgently needed across the LAC region.

Physical properties, such as bulk density and soil compaction, are also essential for evaluating soil health. Higher-SHI soils tend to have lower bulk density and reduced compaction, enabling better root penetration and water infiltration. In contrast, lower-SHI soils often exhibit higher compaction, which can be addressed through practices like subsoiling or the use of cover crops. Soil physical attributes, closely tied to soil structure, are critical to multiple soil functions and must be included in SHI evaluations²¹. Advances in Europe, such as the mapping of soil density for SHI assessment, exemplify the potential for large-scale monitoring initiatives⁴⁷.

Promoting soil management practices that combat degradation is essential for improving soil health at a continental scale. Practices such as cover cropping^{48,49}, no-till farming, pasture reclamation, integrated systems⁴⁵, and traffic control⁵⁰ have proven effective in enhancing soil quality. The development of SHI maps underscores the need for integrated strategies to address organic matter, pH, nutrient levels, compaction, and microbial activity²¹. Such targeted interventions can substantially enhance soil fertility, productivity, and sustainability across diverse agricultural systems as well as environmental management actions⁵².

Challenges and perspectives for comprehensive soil health mapping and assessment

Assessment of SH poses intricate challenges due to ecosystem diversity and the variability of climate conditions, soil types, and agricultural practices^{53–55}. This diversity influences the spatial patterns of SH in LAC and poses a challenge to developing universally applicable assessment methodologies. The lack of standardization in SH measurement methods^{20,35,37} results in heterogeneous datasets, hindering direct comparisons between regions. Climate change further complicates assessments, impacting soil dynamics and necessitating periodic monitoring for parameter adjustments¹³.

Given that SH is a multidimensional concept, a profound understanding of the interactions between soil components and the environment is essential for successful assessments^{2,56}. However, several obstacles must be overcome to comprehensively assess SH on a large scale^{13,22}. These challenges are linked to spatial patterns formed by climate conditions, which influence the dynamics of soil drivers and change them across different scales. Advanced tools like remote sensing and machine learning are essential to address these issues, as they enable the weighting of climate factors specific to different regions of the globe^{26,53}. This task requires multidisciplinary, highly trained staff, a scarce and expensive resource that hinders accurate evaluations²⁹.

Indicator weighting, a critical step in the SH indexing process, should be carefully performed based on well-established scientific principles and literature^{20,46,57}. Data-driven machine learning techniques can be employed to optimize these weights or understand their interactions. Additionally, the utilization of a “digital twin” methodology can facilitate real-time monitoring of SH conditions³⁸.

The methodology presented in this study offers a great potential for scalability and replication in regions outside LAC. By leveraging cloud-based machine learning, advanced remote sensing, and data science, it accommodates large-scale assessments in diverse geographic contexts. While tailored to the unique environmental and socio-economic conditions of LAC, this framework is adaptable. Critical to its replicability is the availability of geospatial data and region-specific expertise for calibrating soil health indicators and weighting them appropriately to local needs. The flexible design of the methodology ensures that, with appropriate adjustments, it can guide soil health assessments in other regions, offering valuable insights into ecosystem functionality and land management. This adaptability is especially pertinent in the face of global challenges like soil degradation and climate change.

Finally, global collaboration is needed to address the challenges of SH assessment^{54,56,58}, which is helpful for standardization in measurement methods. Utilizing advanced technologies while ensuring cost-effectiveness is essential for spatial assessments. Establishing soil monitoring systems and comprehensive databases promotes an understanding of SH dynamics. In this regard, a lack of consistent databases is also a barrier to comprehensive assessment, underscoring the need for robust database systems built through long-term soil monitoring²³.

Achieving standardized protocols for soil data collection, laboratory analysis, and interpretation of indicators is essential for practical SH assessment⁵⁹. For that, farmers, scientists, governments, and stakeholders must be engaged by national and international initiatives (e.g., Soil Health Institute; Brazilian Agricultural Research Corporation (Embrapa)’s SoilBio Network; Center for Carbon Research in Tropical Agriculture (CCARBON); IICA-Living Soils of America (LISAm); Global Soil Health Programme, Coalition of Action 4 Soil Health (CA4SH); Soil Health Benchmarks; European Commission-Directive on Soil Monitoring and Resilience).

Conclusion

Our study showcases the feasibility and scalability of implementing a comprehensive approach based on digital mapping of soil attributes for assessing soil health (SH) in the LAC region at a 90 m resolution. We derived SH indicators from digital maps of soil attributes by utilizing a weighted model based on soil functions, providing detailed spatial information.

The SH map revealed distinct spatial patterns across the LAC regions. Unhealthy soils predominated in drylands arid and savanna regions and are correlated with the high frequency of soil exposure. Densely forested areas in low-elevation quotes exhibited the middle-low SH, evidencing the need to maintain them preserved. Rainy areas and cool temperature zones had the healthiest soils. This behavior reveals the substantial influence of climate factors causing latitudinal patterns in the SH distribution, evidenced by subtropical regions exhibiting the poorest SH (lowest SHI) and equatorial zones (excluding arid regions) displaying healthier soils (highest SHI).

Addressing gaps regarding spatial and temporal lack of data and utilizing innovative methodologies that include empirical, theoretical and experimental models can contribute to a more thorough understanding of SH dynamics in space and time. Identifying healthy soils’ geographic extent and location is critical for food security, biodiversity conservation, and climate change mitigation. Quantifying areas of poor SH is essential to guide policy efforts toward targeted ecosystem restoration.

Material and Methods

Soil data and proxies

Soil health (SH) indicators were carefully selected to reflect the agroecological conditions specific to Latin America and the Caribbean (LAC) and their demonstrated effectiveness in assessing critical soil functions within ecosystems. This selection process involved extensive consultations with regional experts and a thorough review of the latest literature^{2,17,20,60}. Our comprehensive approach can ensure that the chosen indicators are well-suited to address the region’s diverse environmental challenges, which are intrinsically linked to achieving the United Nations Sustainable Development Goals^{6,12}.

Conducting extensive surveys, we gathered research and data from open soil databases in the countries constituting the LAC (Supplementary Table S1). Furthermore, we performed a driven search to reach out to researchers and public organizations seeking to acquire georeferenced soil data from unpublished sources. However, challenges in data acquisition may have arisen due to each institution's internal (restrictive) policies.

Subsequently, we meticulously evaluated the consistency and harmonization of the data. Later, we consolidated the dataset into a unified database and applied the spline method for interpolation at a depth interval of 0–20 cm, as illustrated in Supplementary Fig. S1. It is noteworthy that we specifically focused on the soil attributes that had the highest data availability for mapping, as follows:

- Physical attributes: clay, silt, sand, bulk density (BD), and plant available water (PAW); SSI: Structural stability index; Total porosity (TP); Saturated hydraulic conductivity (K_{sat}). We estimated BD through an improved pedotransfer function⁶¹ and determined PAW utilizing a flux-based approach⁶²;
- Chemical attributes: cation exchange capacity (CEC), nitrogen (N), phosphorus (P), potassium (K), pH in water, and base saturation (V); and
- Biological attributes: C and C_{stock} ⁶³.

We employed the theoretical model 'scorpan,' proposed by Alexander McBratney in 2003²⁸, for mapping the soil attributes. This equation utilizes Jenny's soil formation factors to represent the classes or attributes of the soil (S), expressed as a function (f) dependent on several covariates. These variables include soil properties at a specific point (s), climatic properties of the environment at that point (c), organisms present (o), such as natural vegetation, fauna, or human activity, topography and landscape attributes (r), parent material or lithology (p), the age of the system under consideration (a), and the spatial or geographic position (n). Parsimony-based proxies derived from remote sensing data represented these factors (Supplementary Table S2).

Soil attributes mapping

The geospatial mapping pipeline⁵⁵ implemented in Jupyter Notebook (Python) and Google Earth Engine mapped soil attributes in the 0–20 cm layer at a 90 m spatial resolution. This study undertook data preprocessing for quality assurance, beginning with acquiring remote sensing data. Subsequently, we extracted relevant features and deployed predictive models to establish the correlation between these features and specific soil attributes. The ensuing pipeline spatially mapped the soil attributes, ensuring high precision. We ensured result accuracy by implementing integrated validation steps and presented the outcomes visually for a comprehensive understanding of soil property spatial distribution. The steps include remote sensing data acquisition, data preprocessing, feature extraction, predictive model implementation, spatial mapping of soil attributes, and integrated validation measures.

- I. Sampling of covariates;
- II. Hyperparameter tuning of the Random Forest algorithm through testing 27 combinations/models for each soil attribute;
- III. 10-fold stratified (by biome) cross-validation and calculation of performance metrics;
- IV. Selection of optimal models based on the lowest root mean square error (RMSE) value;
- V. Spatial leave-one-out cross-validation (SLOO-CV) using various buffer sizes (10, 100, 1000, 2000, and 5000 m) to address potential spatial autocorrelation (inflated R^2 values);
- VI. Spatial prediction with stratified resampling (by biome) using 100 repetitions (bootstrapping) and
- VII. Generation of final spatial prediction maps (at a 90 m spatial resolution), including mean values, standard errors, and minimum (5%) and maximum (95%) prediction intervals for each soil attribute in the 0–20 cm layer.

Supplementary Tables S3, S4 detail the observations and prediction performance of Random Forest (RF) models for soil attributes from LAC in the 0–20 cm depth layer. These charts provide an overview of RF models' metrics and coefficient of determination (R^2) for soil attributes from LAC in the 0–20 cm depth layer. R^2 values were computed during the Spatial Leave-One-Out Cross-Validation (SLOO-CV) with different buffer sizes to address potential spatial autocorrelation. In addition, Supplementary Fig. S2 exhibits the maps of soil attributes predicted with 90 m spatial resolution at 0–20 cm depth for LAC. These soil attribute grids generate maps of SH functions and SHI.

Soil health mapping

The assessment of SH followed the three sequential stages outlined in The Soil Management Assessment Framework⁶⁴, a methodology previously validated for Latin American soils²⁰. The stages involved acquiring, interpreting, and integrating the SH indicators, generating a model for SHI applied for every raster pixel, and resulting in an SH map. Therefore, these approaches are based on widely accepted methodologies and applied globally^{35,37}.

Indicators obtention

The first stage involved the selection of indicators following literature recommendations to include at least one indicator representing the soil's chemical, physical, and biological components. Thus, we selected 15 indicators covering these three soil properties available in the LAC for modeling the SH. We derived physical and chemical indicators from the soil maps obtained for LAC in the previous section, and we acquired biological indicators from global soil maps of nematodes⁶⁵ and earthworms³³, both in the density of individuals unity. We ensured a proportional representation of indicators across these components, as suggested by Lehmann², who recommend that at least 20% of the indicators should come from each domain.

This study evaluated SH from the perspective of plant production (agricultural) and environmental protection. Chemical indicators describe the condition of the soil environment and the availability of nutrients for plants and microorganisms. We used pH in water, CEC, and nutrients N, P, K, and base saturation¹⁷. The indicators that represented soil physical-related functions were BD, PAW, TP²⁰, saturated hydraulic conductivity⁶⁶, and aggregate stability⁶⁷. We calculated the last three of them using raster algebra. These indicators mainly reflected germination and plant growth limitations, water infiltration and movement within the soil profile, stress, nutrient transfer, and cycling¹⁷.

Living organisms, utilized as biological indicators, play a role in the breakdown and assimilation of animal and plant residues in the soil. This activity regulates ecosystem nutrient cycling and organic matter⁶⁰. The abundance of individuals that compose the soil biota represents these indicators¹⁷. Due to their sensitivity, they acted as early signs of soil degradation or improvement⁶⁸. Ultimately, soil C stocks influence multiple soil functions critical for planetary functioning⁶⁹.

The indicators meet all key criteria—conceptual, practical, sensitivity, and interpretability¹⁷, and are among the most frequently used in global SH assessments^{2,4,17,20,37,51,70,71}. This balanced set of indicators responds to multiple soil functions and ecosystem services, including plant production (food and energy provision), nutrient cycling, carbon sequestration, buffering against acidity and contamination, water regulation (entry, retention, and release), erosion control, and habitat provision for soil biota^{2,16,20,72}.

Indicators interpretation

We interpreted the SH indicators using non-linear functions (scoring curves), which normalize (score) the values between 0 and 1² (Table 1). The indicators were scored considering the agricultural and environmental functions using the following scoring-curve shapes: 'more is better' (upper asymptotic sigmoid curve ) , 'less is better' (lower asymptotic sigmoid curve ) , and 'optimal midpoint' (Gaussian curve ) . The "more is better" equation was used to evaluate soil nutrients (N, P, K) instead of the "optimal midpoint" because, after careful review of the database, no

Table 1 | Soil health indicators and types of interpretation curves

Indicator	Resolution (m)	Depth (cm)	Unit	Scoring-curve shape	Reference for interpretation
<i>Chemicals</i>					
pH _{water}	90	0–20	Log		18
CEC	90	0–20	mmol _c kg ⁻¹		76
N	90	0–20	g kg ⁻¹		EO
P	90	0–20	mg kg ⁻¹		18
K	90	0–20	mmol _c dm ⁻³		18
V	90	0–20	%		18
<i>Physicals</i>					
BD	90	0–20	g cm ⁻³		77
PAW	90	0–20	cm ⁻³ cm ⁻³		62
TP	90	0–20	cm ⁻³ cm ⁻³		EO
K _{sat}	90	0–20	cm d ⁻¹		78
SSI	90	0–20	%		67
<i>Biologicals</i>					
Carbon	90	0–20	g kg ⁻¹		64
C _{stock}	90	0–20	kg m ⁻²		64
ED	1000	0–15	individuals m ⁻²		79
ND	1000	0–15	individuals m ⁻²		80

EO expert opinion, pH_{water} pH determined in water, CEC cation exchange capacity, P phosphorus, K potassium, V base saturation, BD bulk density, SSI structural stability index, PAW plant available water, TP total porosity, K_{sat} saturated hydraulic conductivity, C_{stock} organic carbon stock, N nitrogen, ED earthworm density, ND nematode density.

excessively high levels were found in this region that would pose an environmental risk.

Integrating scored indicators

We weighted the scored indicators as maps using a model grounded in five soil functions (Eq. 1). We combined these weighted indicators by summing their values to create an integrated soil health index (SHI), as shown in Supplementary Table S5. The resulting SHI provided a relative measure of the soil's potential to perform the functions necessary for its intended use.

$$SHI = \sum_{i=1}^n W_i S_i \quad (1)$$

Where SHI is the soil health index, S_i is the indicator score, n is the number of indicators integrated into the index, and W_i is the weighted value of the indicators.

We assigned each indicator a specific weight (e.g., 0.165) within its corresponding soil function. The soil functions had a similar weight (0.20) when composing the integrated SHI. A framework developed from soil functions, suggested by relevant studies^{20,46,73}, derived every SH indicator's weight used in the modeling. This weighting process and the combination of consolidated literature supported by the expertise of the team of specialists was essential in finding solutions that yielded reliable and reproducible results. The raster algebra considering the weighting values enabled the generation of 90 m maps for each soil function and the integration in a comprehensive SHI map covering the entire LAC area.

Assessing the Soil Health Map

We assessed the relationship between our maps and data by observing the latitudinal patterns. We calculated average values for various parameters, including the SHI, the five soil functions, bare soil frequency²⁶, and above-ground biomass density⁷⁴ across 1-degree latitude bands throughout the LAC. The bare soil frequency indicates the occurrence and frequency of bare surfaces detected by the Landsat series within individual pixels. It is highest in desert regions and lowest in areas with dense vegetation. Greater aboveground living plant biomass generally indicates higher C content and biodiversity levels.

Therefore, we could observe the SHI by the political and environmental division within LAC and by countries and biomes. Crossing the SHI map with ecoregions (biomes) and countries' LAC boundaries vector-based, we generated a Sankey diagram to observe both features by SHI levels across LAC. Five SHI categories represented the SH levels, which ranged from 1 (the worst SHI) to 5 (the best SHI). The Jenks algorithm decided where to set the breakpoints between SHI classes (see Supplementary Note 5). The Jenks natural breaks method optimizes the representation of natural data groupings. This method minimizes within-class variance and maximizes between-class variance, making it a robust tool for defining meaningful SH categories. The resulting classification facilitates the clear presentation and discussion of SH variations across different biomes and countries, thereby improving interpretability. This step provided a comprehensive understanding of SH in the study region, relating it to the socio-economic and environmental issues that impact SH.

The SHI ranges from class 1, representing very poor soil health, to class 5, indicating very good soil health, with increasing functionality, productivity, and provision of ecosystem services. Specifically, SHI classes can be interpreted as follows:

Class 1 - Very poor soil health: these are characterized by severe limitations that critically impair their ability to perform essential functions such as nutrient cycling, water retention, and carbon sequestration. These soils exhibit poor structure, low fertility, and minimal biological activity, making them unsuitable for sustainable agricultural use without extensive intervention. They are highly vulnerable to degradation processes like erosion, compaction, and desertification, often found in arid or overexploited regions where soil cover is sparse or absent. Ecosystem services these soils provide are minimal, posing great challenges for land use. Immediate rehabilitation strategies, such as the application of management practices to control erosion and revert soil C and biodiversity depletion are critical to halt further decline and promote gradual recovery allowing the reintroduction of these areas to agricultural production systems or even to natural restoration or reforestation programs.

Class 2 - Poor soil health: these soils display moderate to severe limitations that restrict their capacity to support agricultural productivity or provide ecosystem services. While slightly better than Class 1 soils, they still suffer from reduced fertility, limited water retention, and poor biological activity and diversity. These soils are more prone to nutrient leaching and erosion, often found in regions transitioning from arid to semi-arid climates or under high anthropogenic pressure. Land use options are constrained to low-intensity agricultural practices, requiring substantial management practices such as liming, fertilization, contour farming, reduced or no-tillage, grazing management and pasture reclamation. Although some ecosystem functions are retained, targeted interventions are necessary to improve and sustain their health over time.

Class 3 - Moderate soil health: these soils exhibit a balance of strengths and weaknesses, performing adequately in some functions while retaining persistent limitations in others. These soils support moderate fertility levels and biological activity, sufficient for sustaining forests, pastures, or crops with proper management. While less susceptible to erosion and soil structural degradation than poorer soils, their water retention (and PAW content) and nutrient cycling capabilities may be suboptimal, requiring interventions like cover cropping, crop rotation or integrated systems to improve soil stability and productivity when cultivated. Found in areas with moderate rainfall or mixed land use, these soils represent transitional

conditions between degradation and sustainability. Proactive management can enhance their functionality, supporting both productive agriculture and ecosystem services.

Class 4 - Good soil health: soils are highly functional, supporting productive agricultural systems and providing key ecosystem services. With good fertility, structure, and water-holding capacity, these soils enable healthy plant growth and efficient nutrient cycling. Biological activity is active and diverse, contributing to resilience against environmental stresses like drought or heavy rainfall. Found in regions with sustainable land management or favorable environmental and geological conditions, these soils require interventions, such as periodic liming and fertilization, conservation agriculture practices, and sustainable pasture and grazing management, to maintain their productivity and ecological value. Their robust functionality makes them well-suited for both agricultural and conservation purposes, serving as a foundation for sustainable land use practices.

Class 5 - Very Good soil health: these represent the pinnacle of soil health, performing exceptionally in all critical functions, from nutrient cycling to water retention and carbon sequestration. These soils are rich in fertility, possess excellent structure, and have high biological diversity and activity, making them ideal for intensive agricultural use or preservation efforts. Their resilience to degradation ensures consistent productivity and ecological stability, even under changing environmental conditions. Often found in regions characterized by favorable climatic and geological conditions to form fertile and well-developed soils associated with minimal human disturbance or well-implemented sustainable practices, these soils provide maximum ecosystem services, including biodiversity support and climate regulation. Maintaining these soils at their peak requires protection through sustainable practices like cover cropping, minimal disturbance, integrated systems, and conservation policies to ensure their long-term viability and ecosystem contributions.

Intrinsic drivers of SHI

We leverage game theory, employing SHapley Additive exPlanations (SHAP) values⁵³, to gain insights into the intrinsic factors that influence the SHI. To achieve this, we applied the TreeExplainer from the 'shap' package⁵³ to an RF model trained on soil indicators, enabling us to estimate SHAP values in the SHI model. The SHAP values provided local explanations for each sample in the dataset. They resulted in five distinct SHI levels based on percentiles (5th, 25th, 50th, 75th, and 95th) for understanding the global model's decision-making process, thus bringing to knowledge the major intrinsic SH drivers.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

The maps generated in this study, including the Soil Health Index (SHI) and soil functions, are publicly accessible. They can be visualized through the Earth Engine application at <https://geocis.users.earthengine.app/view/lac-soil-health> and downloaded at <https://geocis.users.earthengine.app/view/lac-soil-health-download> and <https://esalqgeocis.wixsite.com/english/raul-poppiel-sh4lac>. Additionally, the SHI and SF maps are available as raster files in a public repository hosted on the Zenodo repository at link: <https://zenodo.org/records/1428568575>.

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Author contributions

R.R. Poppiel conceptualized the research, performed data processing and visualization, and was responsible for drafting and revising the manuscript. J.J.M. Novais conducted paper design, formal results analysis and interpretation, contributing substantially to the manuscript's writing and revisions. M.R. Cherubin and J.A.M. Demattê team coordinator, critical revisions, secured research funding, and offered ongoing academic guidance throughout the project. All authors contributed equally to the final review and approval of the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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