

1 A database for global soil health assessment

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14 15 Abstract

16
17 Field studies have been performed for decades to analyze effects of different
18 management practices on agricultural soils and crop yields, but these data have never
19 been integrated together in a way that can inform current and future cropland
20 management. Here, we collected, extracted, and integrated a database of soil health
21 measurements conducted in the field from sites across the globe. The database, named
22 *SoilHealthDB*, currently focuses on four main conservation management methods:
23 cover crops, no-tillage, agro-forestry systems, and organic farming. These studies
24 represent 354 geographic sites (i.e., locations with unique latitudes and longitudes) in
25 42 countries around the world. The *SoilHealthDB* includes 42 soil health indicators and
26 46 background indicators that describe factors such as climate, elevation, and soil type.
27 A primary goal of this effort is to enable the research community to perform
28 comprehensive analyses, e.g., meta-analyses, of soil health changes related to cropland
29 conservation management. The database also provides a common framework for
30 sharing soil health, and the scientific research community is encouraged to contribute
31 their own measurements.
32

33 Background & Summary

34
35 Soil health, sometimes used interchangeably with soil quality, represents the ability
36 of soils to function as a biodiverse organism that sustains terrestrial life (USDA-NRCS,
37 2019), and is often assessed using a combination of physical, chemical and biological
38 indicators¹. Cropland soil degradation due to natural vegetation removal, intensive
39 agricultural operations, and erosion are among the main factors causing declines in soil
40 health and crop yields²⁻⁴. According to a recent report from the Food and Agriculture
41 Organization of the United Nations (FAO), one-third of soils in the world are infertile
42 due to unsustainable land-use management practices⁵. Cropland conservation
43 management practices, including the use of cover crops within rotations and changes
44 from traditional mouldboard or disk tillage to reduced or no-tillage, have been proposed
45 as ways to increase soil carbon and soil health^{6,7}. Many on-site experiments have been
46 conducted to evaluate the effects of conservation management on soil properties, yet
47 there has been little effort to evaluate which indicators should be measured to
48 consistently quantify any resulting improvements in soil health. In addition, studies can
49 differ in their results: as an example, using cover crops during normally fallow seasons

50 can enhance soil organic carbon⁸, though many short-term studies have not found this
51 same result^{9–11}.

52 To better address such uncertainties, systematic reviews and meta-analyses have
53 evaluated the effects of cover crops¹², no-tillage^{13,14}, organic farm¹⁵, and agroforestry
54 systems¹⁶ on crop yield and soil properties. These efforts have generated new insights
55 into soil health dynamics, yet there is still limited understanding of whether and how
56 these findings translate to global scales. Historically and newly published data offer a
57 wealth of information that can support global assessments of how conservation
58 agricultural practices may influence soil health, provided that there is an effective
59 mechanism to record and disseminate this information.

60 To address this gap, we collected studies that compared agricultural production and
61 soil properties under traditional management strategies with those under conservational
62 management practices. Publications that meet specific criteria were digitized and the
63 data were integrated into a global soil health database that we have named *SoilHealthDB*.
64 This web-based, open source dataset can be continuously updated by including newly
65 published and even provisional data. The dataset can be used to perform statistical
66 analyses (e.g., meta-analyses) on specific soil health indicators or agronomic responses.
67 *SoilHealthDB* provides a common soil health framework for sharing and integrating
68 field measurements and related information, and thereby offers valuable information
69 for farmers, agency personnel, and scientists as they plan and evaluate cropland
70 management.

71

72 **Methods**

73 **Data collection**

74 *SoilHealthDB* currently includes 46 background indicators (Online-only Table 1)
75 and 42 soil health indicators (Online-only Table 2)¹. To identify relevant studies, we
76 conducted a systematic literature search for field comparisons between traditional and
77 conservational management practices. We initially targeted four main conservational
78 management methods: cover cropping (CC), no-tillage (NT), organic farming (OF), and
79 agro-forestry systems (AF) (Table 1).

80 Publications were searched and collected from three sources: (1) an online literature
81 search; (2) the Soil Health Institute “Research Landscape Tool”, which compiles soil
82 health results into a searchable database and includes publication and research projects¹⁷;
83 and (3) cited papers from previous meta-analyses or review papers^{12,15,18,19}. For the
84 online literature search we used the ISI Web of Science, Google Scholar, and the China
85 National Knowledge Infrastructure (CNKI). We used the keywords “soil health” or
86 “soil quality” and “conservation management”, “cover crop”, “no-till”, “organic farm”,
87 or “agroforestry systems” when performing the literature search. Papers from peer-
88 reviewed journals, conference collections, theses, and dissertations were included. No
89 other restrictions or filtering criteria were used (e.g., we included eligible papers in all
90 languages and with all publication dates). We collected a total of more than 500 papers;
91 we then used the following criteria to determine whether the publication would be
92 included in this study: (1) experiments were conducted in the field or at a research
93 station; (2) the publications compared controls (i.e., traditional management) and
94 treatments (i.e., conservational management); (3) publications provide at least one
95 comparison of soil health indicators between controls and treatments (Online-only
96 Table 2). Within these constraints, 321 papers were extracted and integrated into the
97 *SoilHealthDB*.

98 Data were digitized from tables and figures. The software Data Thief (version III)
99 ²⁰ was used to read the data from figures. Background information was extracted from
100 the publications and fit into 46 background indicator categories (Online-only Table 1).
101 Whenever latitude and longitude were not reported in the literature, the site name was
102 entered into the website (<https://www.findlatitudeandlongitude.com>) to estimate
103 location. Whenever elevation was missing from the original paper, it was identified by
104 latitude and longitude (<https://www.freemaptools.com/elevation-finder.htm>). In total,
105 5,907 comparisons were collected from across the globe (Figure 1), for a mean of
106 approximately 20 comparisons per study. As many studies reported multiple
107 comparisons, we needed to identify if those comparisons were independent of one
108 another. We therefore allocated a unique experiment ID to a comparison if the cover
109 crop group, cash crop group, site, tillage, fertilization, soil depth, termination, or
110 rotation were different from other comparisons (Figure 2). This process resulted in a
111 total of 1,407 experiments that were assumed to be independent of each other.

112 Data processing

113 After the location information was carefully checked, the climatic regions for all
114 sites were identified according to climate Koppen classification²¹, using the latitude and
115 longitude (for a detailed description please see the ‘Data Records’ section provided in
116 the supplemental R code²²). All missing MAT and MAP values were estimated using a
117 global air temperature and precipitation dataset provided by the Center for Climate
118 Research at the University of Delaware²³. The MAP and MAT were calculated based
119 on the monthly precipitation and temperature between 1961 and 2015. Soil texture was
120 grouped into coarse (sand, loamy sand, and sandy loam), medium (sandy clay loam,
121 loam, silt loam, and silt), and fine (clay, sandy clay, clay loam, silty clay, and silty clay
122 loam) textures based on the Cornell Framework²⁴.

123 The cash crops were grouped into corn, soybean, wheat, other monoculture, corn-
124 soybean rotation (CS), corn-soybean-wheat rotation (CSW), and other rotation of more
125 than two cash crops (ROT). The cover crops were grouped into broadleaf, grass, legume,
126 mixture of two legumes (LL), mixture of legume and grass (LG), mixture of two cover
127 crops other than LL or LG (MOT), and other mixtures of more than two cover crops
128 (MTT). Soil sampling depths were grouped into 0-10 cm, 0-20 cm, 0-30 cm, and 30-
129 100 cm (Figure 3). It should be noted that the user can regroup the cash crop, cover crop,
130 and soil sampling depth according their research objectives.

131 The number of replications and standard deviations (SD) were compiled from the
132 publications when possible. When the studies reported standard error (SE), coefficient
133 of variation (CV), or confidence interval (CI) rather than SD, SD was calculated using:

$$134 \quad SD = SE \times \sqrt{n} \quad (1)$$

135 where n is the number of observations.

136 SD was calculated from CV as:

$$137 \quad SD = CV \times mean \quad (2)$$

138 and from the CI as:

$$139 \quad SD = |CI - mean| / (2Z_{\alpha/2}) \times \sqrt{n} \quad (3)$$

140 where $Z_{\alpha/2}$ is the Z score for a given level of significance, α . $Z_{\alpha/2}$ is equal to 1.96 when
141 $\alpha = 0.05$ and 1.645 when $\alpha = 0.10$.

142 Soil organic carbon (SOC) data were reported as carbon stocks (Mg/ha). When
143 applicable, SOC was calculated based on SOC concentrations (SOC%) and soil bulk
144 density using:

$$145 \quad SOC = SOC_{\%} \times h \times 100 \times BD \quad (4)$$

146 where h represents soil sampling depth (meter), and BD represents soil bulk density
147 (Mg/m³).

148 SOC sequestration rate (SOC_{seq}) was calculated in terms of (Mg/ha/yr) using:

$$149 \quad SOC_{seq} = (SOC_{cc} - SOC_{background}) \div y \quad (5)$$

150 where SOC_{cc} is the soil carbon stocks under CC treatments (Mg/ha), SOC_{background} is the
151 soil carbon stock either under background conditions or under the no cover crop controls
152 (Mg/ha), and y represents years after CCs.

153 **Code availability**

154 All the data processing and data visualization were conducted using R (version
155 3.5.1)²⁵. The source code is available on figshare²². The code is detailed with
156 instructions for users. Generally, the *function.R* file (under *RScript* folder) defined
157 several functions to obtain background information from external datasets, as well as
158 the function to plot the samples spatial distribution (Figure 1). The
159 *SoilHealthDB_quality_check.R* file (under *RScript* folder) intends to check the data
160 quality, and to explain how some soil health indicators are grouped based on the basic
161 information. We also created a markdown file (*SHDB.Rmd*), which described the
162 analysis and generated figures (Figure 1, 4, and 5) for this study. All the code and data
163 used are available in figshare²² and GitHub
164 (<https://github.com/jinshijian/SoilHealthDB>).

165

166 **Data records**

167 The data and R code can be downloaded in figshare²²; there are two folders, named data
168 and RScripts, when ‘SoilHealthDB.zip’ is unzipped. ‘SoilHealthDB_V1.xlsx’ in the
169 data file currently includes 5,907 rows and 268 columns, which were retrieved from
170 321 papers (for the detailed reference list please refer to ‘References’ under
171 ‘SoilHealthDB_V1.xlsx’²²). Each column corresponds to one data point of either
172 background information or soil health indicator, and each row includes as many as 42
173 comparisons between treatments and controls (if all soil health indicators have data).
174 The names, attributes, and descriptions of the background information and soil health
175 indicators are presented in online-only Tables 1 and 2. It should be noted that different
176 measurements and/or units may be involved in the same soil health indicator (e.g., soil
177 total nitrogen, soil organic nitrogen, or soil inorganic nitrogen are reported in different
178 papers to represent the soil nitrogen indicator, ID 5 in Online-only Table 2); therefore,
179 it is important that measurement objectives, units, and other detailed descriptions are
180 recorded in the comments columns. It should also be noted that for some soil health
181 indicators (e.g., CH₄ and N₂O emission), we were only able to extract limited numbers
182 of comparisons, which may restrain the ability of those data to be used in further
183 analyses. ‘SoilHealthDB_V1.csv’ is a simplified version of ‘SoilHealthDB_V1.xlsx’,
184 with only soil health background and indicator information kept (e.g., all the description
185 sheets were not kept). There are two R scripts in the ‘RScripts’ folder: the
186 ‘SoilHealthDB_quality_check.R’ script includes code for quality check of the
187 ‘SoilHealthDB’, and the ‘functions.R’ script defines several functions, including one to

188 generate the location of the site in ‘SoilHealthDB’. The SoilHealthDB_V1.csv file is to
189 be used when running the R codes.

190 **Technical validation**

191 Quality control was performed to check the fidelity of the data to the original source.
192 Each paper was carefully read at least twice, and special attention was paid to the tables,
193 figures, and method sections, where most of the soil health indicator comparisons and
194 background information were located. Before a new paper was extracted, we first used
195 the bibliography database manager Mendeley to check whether it was a duplicate of
196 previous papers (for details, please see the supplemental reference document). After the
197 data extraction, we compared the digitized data against the tables or figures from the
198 original paper once again to make sure the data were loaded correctly.

199 After the data extraction, we examined data quality using R (version 3.5.1)²⁵. The
200 formats of each column (numerical or string) were checked to correct any mistyping in
201 the numerical columns (e.g., checking all soil health indicators and some background
202 information columns like latitude and longitude). For each soil health indicator, we
203 calculated the response ratio (RR), which is the value of treatment divided by the value
204 of control, e.g., for cover crop studies $RR = \ln(x_{cc}/x_{nc})$, where x_{cc} is the mean parameter
205 value under cover crops and x_{nc} is the mean parameter value under no cover controls.
206 We then plotted the frequency distribution of response ratio for each soil health
207 indicator, and returned to the original articles to verify any extreme values that were
208 identified in this process. We also visualized the data distribution for background
209 columns that contained numeric values (e.g. latitude, elevation) and manually checked
210 the outliers by validating them against the original papers. For the location of each site,
211 we plotted the latitude and longitude by country and checked whether there were sites
212 from a specific country that fell outside its border. For those sites, we checked the
213 extracted latitude and longitude information with location information from the original
214 paper (e.g., site name, country name). For some sites located near to coastal areas, a few
215 sites were reported to exist in the sea, likely due to insufficient precision in reported
216 values. For these sites, we slightly corrected the longitude and latitude to the nearest
217 point on land.

218 **Linkages to external data sources**

219 The studies compiled thus far in *SoilHealthDB* rarely reported potentially important
220 soil properties (e.g., cation exchange capacity, CEC) and background information (e.g.,
221 mean annual temperature, MAT, and mean annual precipitation, MAP). Similarly, some
222 soil attributes such as soil taxonomy were classified differently between regions,
223 making it difficult to compare this information. To resolve those issues, we associated
224 our database with external data sources (by latitude and longitude; for details please see
225 the code in the repository). We linked our data with Koppen²¹ classification ($0.5^\circ \times 0.5^\circ$
226 resolution), a global air temperature and precipitation dataset ($0.5^\circ \times 0.5^\circ$ resolution)²³,
227 and the Harmonized World Soil Database v1.2 (HWSD, $0.05^\circ \times 0.05^\circ$ resolution)^{26,27}.
228 We then analysed all samples for their soil type, using the World Reference Base (WRB)
229 classification system^{26,27}, and for their climatic attributes (Figure 4).

230 Samples from *SoilHealthDB* covered all four climate types, with the majority of
231 sites located in temperate areas and relatively few sites located in arid areas (Figure 4a).
232 Sites within the *SoilHealthDB* had somewhat different distributions for MAT and MAP
233 as compared to global distributions (Figure 4b and c), in part because we only included
234 locations with MAT between -5°C and 35°C so as to exclude climates not conducive
235 to crop production. The MAT from *SoilHealthDB* sites followed an approximately

236 normal distribution, with the most common temperatures occurring between 5 and 20 °C.
237 In contrast the global MAT peaked between 20 and 30 °C. The majority of sites in
238 *SoilHealthDB* had MAP between 500 and 1500 mm, while global MAP followed a
239 gamma distribution with a greater proportion of area having < 500 mm MAP.
240 *SoilHealthDB* sites covered 21 out of 32 soil taxonomic groups in the WRB soil
241 classification system^{26,27} (Figure 4d).

242 Only 11 studies reported soil CEC (thus representing approximately 4% of all
243 studies in *SoilHealthDB*), for a total of 54 independent records. There thus exists a
244 paucity of direct CEC measurements in *SoilHealthDB*. However, we were able to
245 estimate CEC for all sites using the HWSD soil database (Figure 5a). Cation exchange
246 capacity (CEC) distributions were similar between *SoilHealthDB* sites and the global
247 HWSD soil database (Figure 5b), suggesting that samples in the *SoilHealthDB* properly
248 represent soil and climatic characteristics for regions conducive to agricultural
249 production.

250 Finally, because attributes such as texture and CEC are important for interpreting
251 soil health, we encourage future submissions to record these types of information to the
252 extent possible. We also encourage use of the WRB taxonomy for all samples, as a way
253 to enhance the global applicability of this database.

254 **Usage Notes**

255 In the *SoilHealthDB*, the measurement objectives and units between each
256 comparison (control vs. treatment within same row) will always be the same. However,
257 each soil health indicator may have multiple measurement objectives and therefore
258 involve multiple units (e.g., a researcher may measure soil total nitrogen in one site and
259 measure organic nitrogen in another site). Detailed information about measurement
260 objectives and units are recorded under the comments column. The user should always
261 check the comments before data processing and analysis; otherwise, without data
262 filtration and unit conversion only response ratios should be analysed. We recommend
263 that users download and explore the database using the provided R code, as the code
264 includes explanations and instructions. The user can contact the corresponding author
265 with questions on understanding the code and using the data.

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280 meta-analysis. The code and the *SoilHealthDB* are available on figshare
281 (<https://doi.org/10.6084/m9.figshare.8292176>) and GitHub
282 (<https://github.com/jinshijian/SoilHealthDB>); those items can be used for individual,

283 academic, research, and commercial usage, and can be repackaged or sold without
284 written permission.

285

286 **Author contributions**

287 Jinshi Jian and Ryan D. Stewart conceived the design of the data framework. Jinshi
288 Jian and Xuan Du extracted and integrated the data from papers to the *SoilHealthDB*.
289 Jinshi Jian drafted the manuscript, and all authors revised and approved the manuscript.

290

291 **Competing interests**

292 The authors declare no competing interests.

Figures

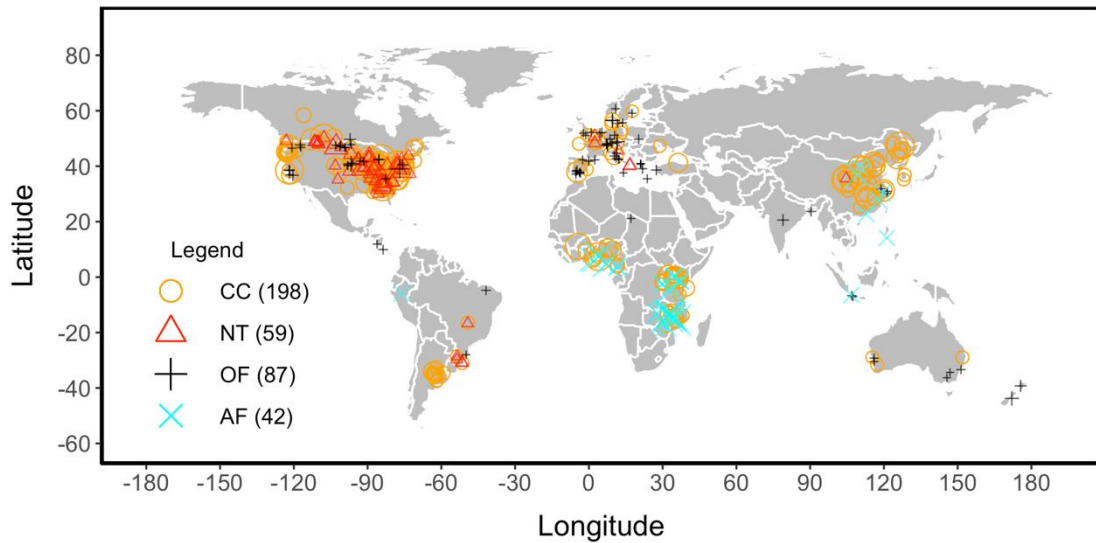


Figure 1. The spatial distribution of sites from cover cropping (CC), no-tillage (NT), organic farming (OF), and agro-forestry systems (AF) across the globe. The numbers in the parentheses represent the number of sites reporting data for each different conservation management method. Symbol sizes represent the number of comparisons in each site.

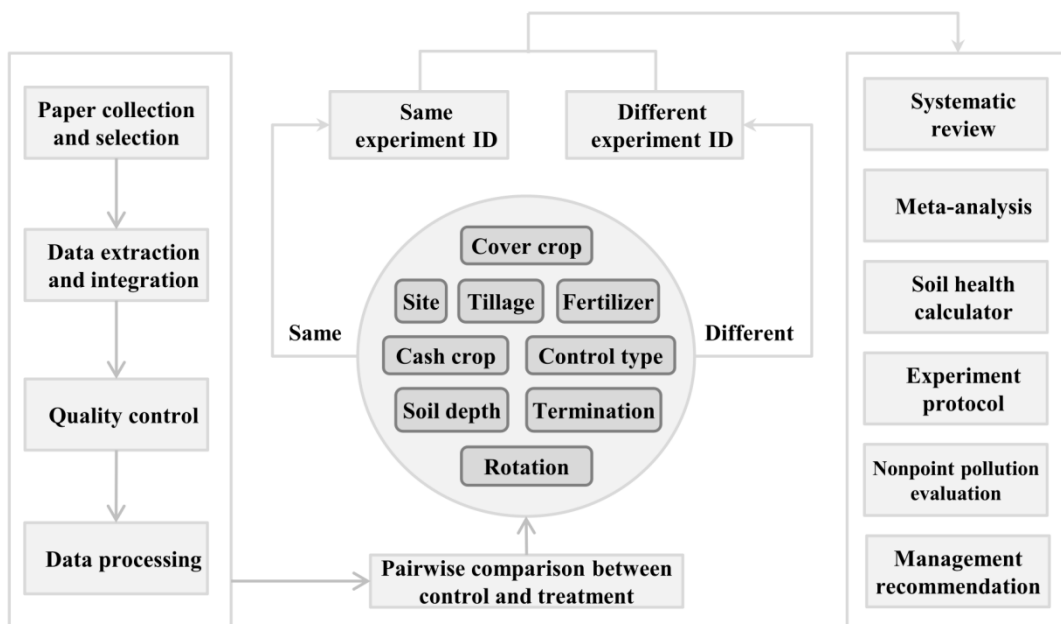


Figure 2. Diagram detailing the procedures for data integration, experiment ID allocation, and potential uses that the database can support. Unique experiment IDs were given to pairwise comparisons if the cash crop, site, tillage, fertilizer level, cover crop, soil sampling depth, cover crop termination, and cash crop rotation was different from other comparisons; otherwise, comparisons who had the same information for one or more of those categories received the same experiment ID (middle panel).

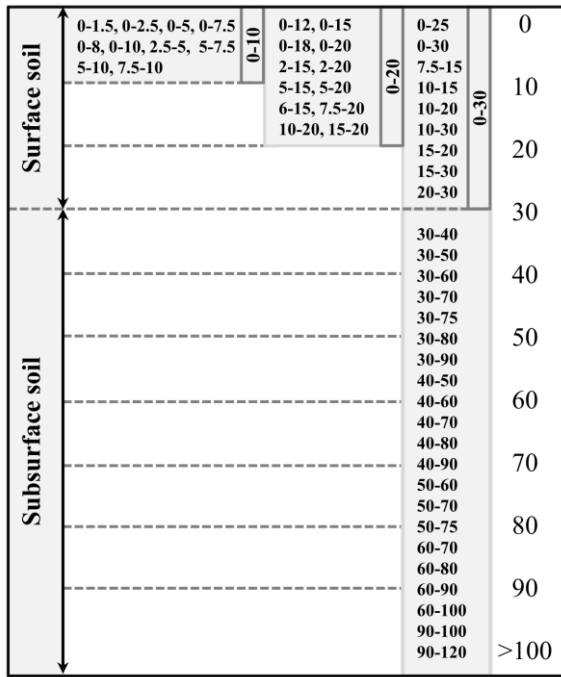


Figure 3. Diagram detailing how soil sampling depths were separated into 0-10 cm, 0-20 cm, 0-30 cm, and >30 cm groups.

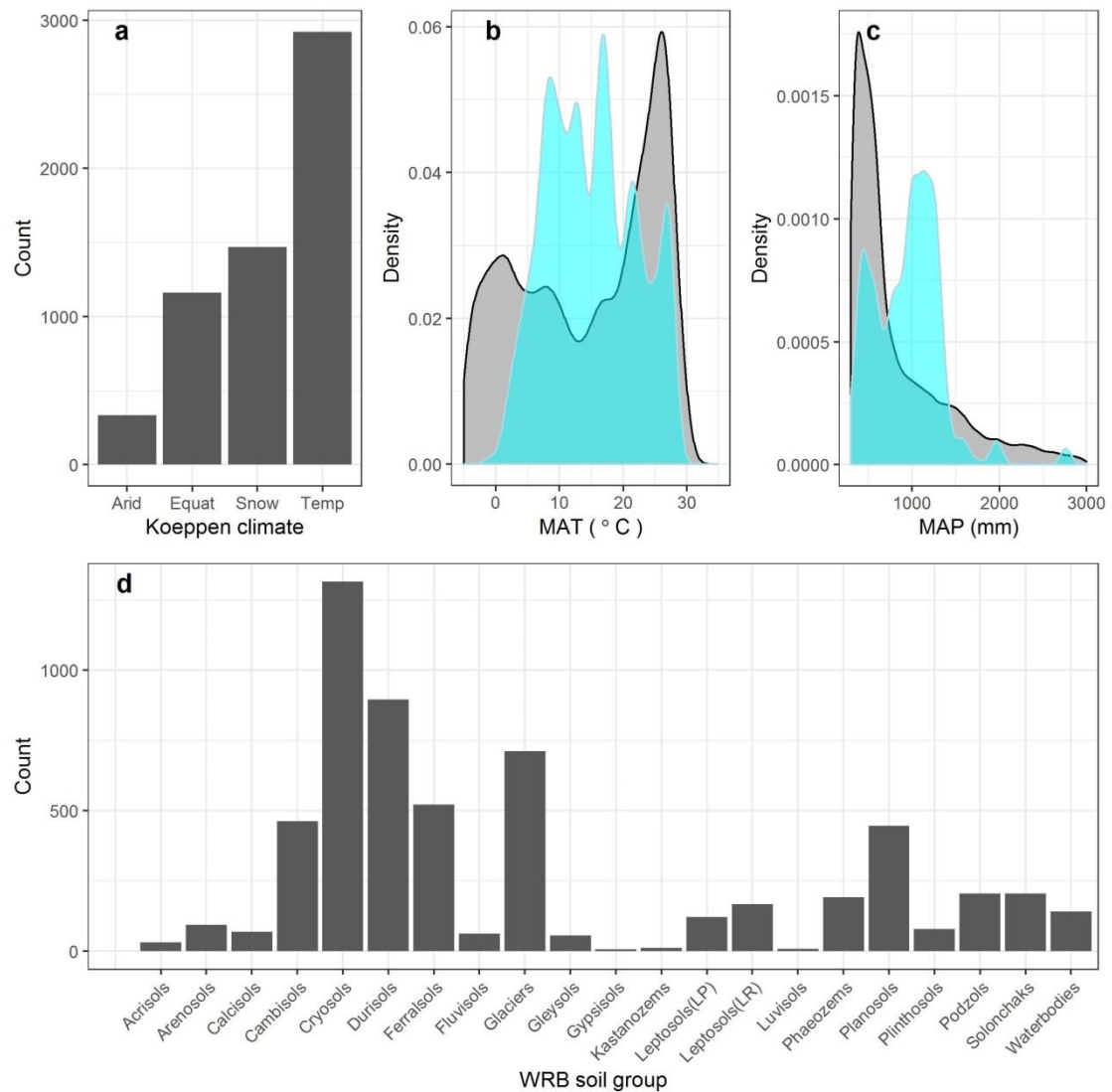


Figure 4. Representation of SoilHealthDB samples in different climate and soil types. Distributions of SoilHealthDB samples values across different parameters. Analyzed distributions include: (a) different climate types; (b) mean annual temperature (MAT); (c) mean annual precipitation (MAP); and (d) different WRB soil groups. Note that in (a) Equat – equatorial and Temp – temperate; in (b) and (c) the light blue represents samples from SoilHealthDB and gray represents global values from the Harmonized World Soil Database v1.2 (for details please see references^{26,27}).

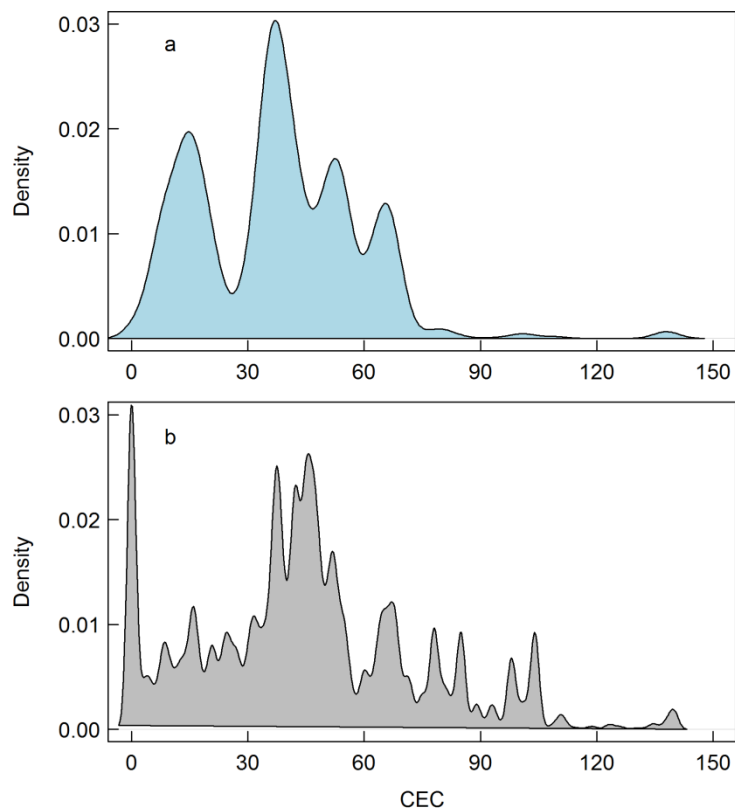


Figure 5. Distribution of cation exchange capacity (CEC) values. Densities are calculated for (a) samples from SoilHealthDB compared with (b) global soils, based on values obtained from the Harmonized World Soil Database v1.2.

Table 1. Conservation type included in *SoilHealthDB*.

Conservation type	Description
Cover crop (CC)	In conventional row crop farming systems, the soil surface often is left bare after harvesting and thus may cause soil erosion, leaching, and decreases in SOC ²⁻⁴ . A cover crop is a plant grown during the fallow season. Grasses or legumes are the major types of cover crops but other green plants such as brassicas. Cover crops are grown primarily for benefit of the soil rather than for crop yield, though cash crop yield increases can result from this practice ²⁸ .
No-tillage (NT)	No-tillage (also named no-till, zero tillage, and direct drilling) is a way of growing crops with minimal soil disturbance. Benefits of no-tillage include: reduced soil erosion, runoff, and leaching; improved soil infiltration; and increased soil organic carbon ¹⁴ .
Agriculture forest system (AF)	Agriculture forest system (also called agro-forestry) is a farmland management practice that combines trees or shrubs with crops or pastures. Benefits of agriculture forest systems include prevention of soil erosion and increased biodiversity. In sub-Saharan Africa and in parts of the United States, agriculture forest systems have been successful applied ¹⁶ .
Organic farming (OF)	Organic farming uses organic fertilizers (e.g., compost manure, green manure, and bone meal) rather than inorganic chemical fertilizers and pesticides. Organic farming can lead to increased soil carbon concentrations ¹⁵ .

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