Improving Latin American Soil Information Database for Digital Soil Mapping enhances its usability and scalability.

Sergio Diaz-Guadarrama[1], Viviana M. Varón-Ramírez[2,3], Iván Lizarazo[1] Mario Guevara[2,4,5], Marcos ~~Angelini[5]~~Angelini[6], Gustavo A. Araujo-~~Carrillo[6]~~Carrillo[3], Jainer Argeñal[7], Daphne Armas[8], Rafael A. Balta[9], Adriana Bolivar[10], Nelson Bustamante[11], Ricardo O. Dart[12], Martin Dell Acqua[13], Arnulfo Encina[14], Hernán Figueredo[15], Fernando Fontes[13], Joan S. Gutierrez-Diaz[16], Wilmer Jiménez[17], Raúl S. Lavado[18], Jesús F Mansilla-Baca[12], Maria de Lourdes Mendonça-Santos[12], Lucas M. Moretti[19], Iván D. ~~Muñoz[20]~~Muñoz[10], Carolina ~~Olivera[5]~~Olivera[6], Guillermo ~~Olmedo[5]~~Olmedo[6], Christian ~~Omuto[5]~~Omuto[6], Sol ~~Ortiz[21]~~Ortiz[20], Carla ~~Pascale[22]~~Pascale[21], Marco ~~Pfeiffer[23]~~Pfeiffer[22], Iván A. ~~Ramos[24]~~Ramos[23], Danny ~~Ríos[25]~~Ríos[24], Rafael ~~Rivera[26]~~Rivera[25], Lady M. ~~Rodriguez[20]~~Rodriguez[10], Darío M. ~~Rodríguez[27]~~Rodríguez[26], Albán Rosales[27], Kenset Rosales[28], ~~Kenset Rosales[29]~~, Guillermo ~~Schulz[27]~~Schulz[26], Víctor ~~Sevilla[30]~~Sevilla[29], Leonardo M. ~~Tenti[27]~~Tenti[26], Ronald ~~Vargas[5], Viviana M. Varón-Ramírez[2,6]~~Vargas[6], Gustavo M. Vasques[12], Yusuf ~~Yigini[5]~~Yigini[6], Yolanda Rubiano[1].

[1]Departamento de Agronomía, Facultad de Ciencias Agrarias. Universidad Nacional de Colombia, Bogotá, Colombia
[2]Centro de Geociencias - Universidad Nacional Autónoma de México Campus Juriquilla, Querétaro, 76230, México.
[3]~~University~~Corporación Colombiana de Investigación Agropecuaria AGROSAVIA, C.I. Tibaitatá, Bogotá, CO-0571, Colombia
[4]University of California, Riverside, Department of Environmental Sciences, Riverside CA. 92507, USA.
[4]~~United~~[5]United States Department of Agriculture, Soil Salinity National Laboratory, Riverside CA. 92507, USA.
[5]~~FAO~~[6]FAO, Vialle de Terme di Caracalla, Rome, Italy
~~[6]Corporación Colombiana de Investigación Agropecuaria AGROSAVIA, C.I. Tibaitatá, Bogotá, CO-0571, Colombia~~
[7]Facultad de Ciencias/ Universidad Nacional Autónoma de Honduras, Honduras.
[8]Departamento de Agronomía, Edif. CITEIIB. Universidad de Almería. Almería, 04120, España
[9]Dirección General de Asuntos Ambientales Agrarios, Ministerio de Desarrollo Agrario y Riego, Perú
[10]Subdirección Agrología, Instituto Geográfico Agustín Codazzi, Bogotá, Colombia
[11]Servicio Agrícola y Ganadero, Santiago de Chile, Chile
[12]Embrapa Solos, Rio de Janeiro, 22460-000, Brasil.
[13]Direccion General de Recursos Naturales, Ministerio de Ganadería, Agricultura y Pesca, Montevideo, Uruguay
[14]Facultad de Ciencias Agrarias de la Universidad Nacional de Asunción, Asunción, Paraguay
[15]Sociedad Boliviana de la Ciencia del Suelo, La Paz, Bolivia.
[16]Department of Agroecology, Faculty of Science and Technology, Aarhus University, Tjele, DK-8830 Denmark
[17]Ministerio de Agricultura y Ganadería, Quito, 170516, Ecuador.
[18]Facultad de Agronomía e INBA (CONICET/UBA), Universidad de Buenos Aires, Buenos Aires, 1417, Argentina.
[19]Estación Experimental Agropecuaria Cerro Azul, Instituto Nacional de Tecnología Agropecuaria, Misiones, Argentina.
~~[20]Subdirección de Geografía, Instituto Geográfico Agustín Codazzi - IGAC, Bogotá, 111321,~~ [20]Secretaría~~Colombia~~
~~[21]Secretaría~~ de Agricultura y Desarrollo Rural, México.
~~[22]Ministerio~~[21]Ministerio de Agricultura, Ganadería y Pesca (MAGYP), Argentina
~~[23]Departamento~~[22]Departamento de Ingeniería y Suelos, Facultad de Ciencias Agronómicas, Universidad de Chile, Santiago, Chile.
~~[24]Instituto~~[23]Instituto de Investigación Agropecuaria de Panamá, Ciudad de Panamá, Panamá
~~[25]Departamento~~[24]Departamento de Ciencias del Suelo y Ordenamiento Territorial, Universidad Nacional de Asunción, Paraguay.
~~[26]Ministerio~~[25]Ministerio de Medio Ambiente, Santo Domingo, República Dominicana

Con formato: Color de fuente: Automático, Superíndice

[27]~~Instituto~~[26]Instituto de Suelos (CIRN), Instituto Nacional de Tecnología Agropecuaria, Hurlingham, Buenos Aires, B1686, Argentina.
[28]~~Instituto~~[27]Instituto de Innovación en Transferencia y Tecnología Agropecuaria, San José, Costa Rica
[29]~~Ministerio~~[28]Ministerio de Ambiente y Recursos Naturales, Guatemala.
[30]~~Universidad~~[29]Universidad Central de Venezuela, Maracay, Venezuela.

Correspondence to: Sergio Díaz (sediazg@unal.edu.co), Mario Guevara (mguevara@geociencias.unam.mx)

Abstract. Spatial soil databases can help model complex phenomena in which soils are decisive, for example, evaluating agricultural potential or estimating carbon storage capacity. The Soil Information System for Latin America and the Caribbean, SISLAC, is a regional initiative promoted by the FAO's South American Soil Partnership to contribute to the sustainable management of soil. SISLAC includes data coming from 49,084 soil profiles distributed unevenly across the continent, making it the region's largest soil database. In addition, there are other soil databases in the region with about 40,000 soil profiles that can be integrated into SISLAC and improve it. However, some problems hinder its usages, such as the quality of the data and its high dimensionality. The objective of this research is ~~twofold. First, to~~ evaluate the quality of the SISLAC ~~and its~~ data ~~values and~~ and the other available soil databases to generate a new~~,~~ improved version that meets the minimum quality requirements to be used by different interests or practical applications ~~Second, to demonstrate the potential of improved soil profile databases to generate more accurate information on soil properties, by conducting a case study to estimate the spatial variability of the percentage of soil organic carbon using 192 profiles in a 1473 km^2 region located in the department of Valle del Cauca, Colombia.~~. The ~~findings~~results show that 15 ~~percent~~% of the existing soil profiles had an inaccurate description of the diagnostic horizons and 17% of the additional profiles already existed in SISLAC, a total of 32% of profiles were excluded for these two reasons. Further correction of an 4.5 percent additional of existing inconsistencies improved overall data quality. The improved database consists of ~~41,691 profiles and is available for public use at https://doi.org/10.5281/zenodo.6540710 (Díaz-Guadarrama, S. & Guevara, M., 2022). The updated profiles were segmented using algorithms for quantitative pedology to estimate the spatial variability. We generated segments one centimeter thick along with each soil profile data, then the values of these segments were adjusted using a spline-type function to enhance vertical continuity and reliability. Vertical variability was estimated up to 150 cm in depth, while ordinary kriging predicts horizontal variability at three depth intervals, 0 to 5, 5 to 15, and 15 to 30 cm, at 250 m spatial resolution, following the standards of the GlobalSoilMap project. Finally, the leave-one-out cross-validation provides information for evaluating the kriging model performance, obtaining values for the RMSE index between 1.77% and 1.79% and the R^2 index greater than 0.5. The results show the usability of SISLAC database to generate spatial information on soil properties and suggest further efforts to collect a more significant amount of data to guide sustainable soil management.~~66,746 profiles and is available for public use at https://doi.org/10.5281/zenodo.7876731 (Díaz-Guadarrama, S. & Guevara, M., 2023). This revised version of SISLAC data offers the potential to generate information that helps decision-making on issues in which soils are decisive. It can also be used to plan future soil surveys in areas with low density or where updated information is required.

Con formato: Inglés (Reino Unido)

1 Introduction

Soil is a three-dimensional natural body consisting of strata called horizons when there are chemical, biological, and even physical relations (i.e., transference of components or products of their alteration among them) or simply layers when they are a consequence of successive deposition of different sediments. Both, horizons and layers are a mixture of degraded mineral materials, organic material, air, and water (Bockheim et al., 2005). Soil is a product of the soil itself (such a point information on a site), climate, organisms, topography, parent material, time, and spatial position, also known as the SCORPAN factors of soil formation (Mcbratney et al., 2003). The soil provides various ecologic or productive contributions besides the obvious importance as a critical factor in food production, e. g. in urban ecosystem services (such a water buffering capacity of open areas), human health (breakdown of toxic contaminants), or climate regulation through carbon storage (Otte et al., 2012). Its sustainable management is of the utmost importance in the main environmental challenges such as food security, climate change, and the loss of biodiversity (Dewitte et al., 2013). Soil data are an essential starting point to reach an adequate level of knowledge about soil status, raise awareness about its importance and preserve this valuable resource (Bouma et al., 2012). Digital soil data (such as soil profiles) are in great demand as inputs to, for example, estimate the potential of agricultural land (Amirinejad et al., 2011; Bini et al., 2013; Owusu et al., 2020); in addition, their availability is key to assess soil functions such as water and climate regulation, energy supply and biodiversity (Greiner et al., 2017). Greater diffusion of soil information has substantial benefits in disciplines such as agricultural sciences by allowing better estimation of current and future crop productivity or identifying constraints and risks of land degradation (FAO & IIASA, 2009; Hopmans et al., 2021; Paterson et al., 2015). FAO indicates that more and better soil data can drive achievements in the fight against poverty and hunger as well as to advance sustainable development(FAO, 2017).

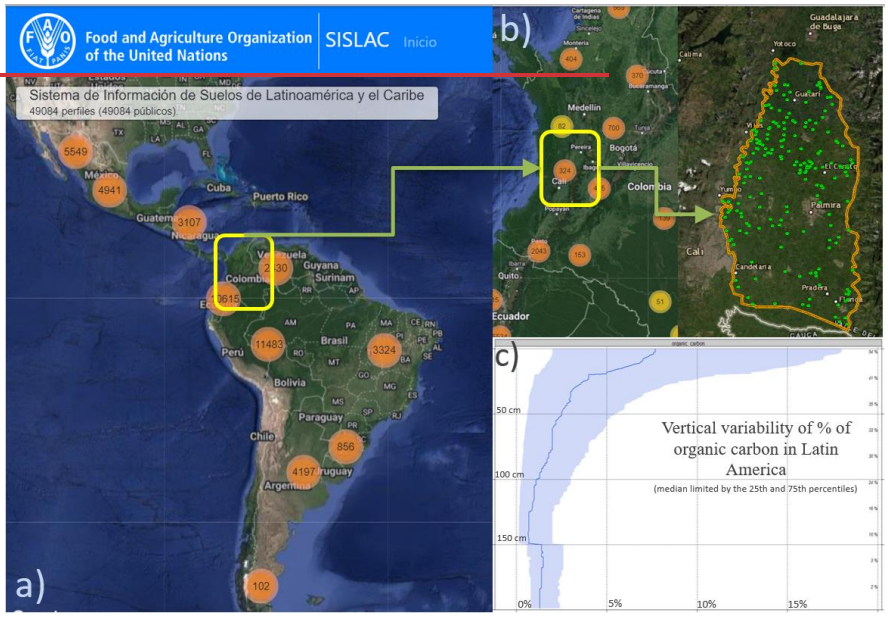
Technological advances and increased computing capabilities have led to the development of soil databases at regional and global scales (Hendriks et al., 2019; Keskin et al., 2019; Rossiter, 2018). Global databases such as the World Soil Information Service, WoSIS (Batjes et al., 2017, 2020), or World Inventory of Soil Property Estimates, WISE (Batjes, 2016), regional databases such as Soil Profiles in Africa (Leenaars, 2013), as well as national ones such as SISINTA in Argentina (Angelini et al., 2018), Harmonized Soil Database of Ecuador 2021 (Armas et al., 2022) or IRAKA in Colombia (Araujo-Carrillo et al., 2021) exist. These datasets are an example of efforts at different levels to have soil profile data that helps to support decision-making in problems involving this resource's management. Organizations such as FAO, the Global Soil Partnership (GSP), and the Latin America and the Caribbean Soil Partnership (LACS), emphasize the need to preserve such data due as, in some parts of the world, soil survey data are the only source of information available (Beaudette & O'Geen, 2009; Hengl & Macmillan, 2019).

The mentioned databases allow scientists to generate information on soil properties such as organic carbon (SOC). SOC is one of the most important chemical properties related to soil fertility and climate regulation, the key to multiple functions in ecosystem services (Owusu et al., 2020). Global projects such as the FAO Organic Carbon Map (FAO & ITPS, 2018), national projects in Brazil (Gomes et al., 2019), Ghana (Owusu et al., 2020), Cameroon (Silatsa et al., 2020) or regional projects in

Andalusia, Spain (Armas et al., 2017), or in paramo ecosystem soils in Colombia (Gutierrez et al., 2020); have been some of the works that have estimated SOC (in its vertical or horizontal dimensions) from soil databases.

Soil Information System for Latin America and the Caribbean, SISLAC, is an initiative coordinated and financed by the FAO's Global Soil Partnership to contribute to the sustainable management of this resource in the region (SISLAC, 2013). SISLAC (Fig. 1a) has data on almost 50,000 soil profiles and 140,000 horizons and layers, making it the most extensive database in the region. The data includes a description of the site for each profile, its spatial location, the layers that comprise it, its physical and chemical properties, data provider, and metadata. In addition to SISLAC, there are other soil databases available in the region that should be analyzed and integrated with it, in order to improve it.

When analyzing available data, it is evident that some of them present inconsistencies due to the high heterogeneity of sources that provide such data. These inconsistencies can be due to, for example, old descriptions using obsolete description systems or errors in transcriptions from field to office. So, if they are not corrected, the analysis results will have a high degree of uncertainty and inaccuracies, primarily since the performance of a model depends on the quality of the training data (Garg et al., 2020). Data quality is a multidimensional concept involving management, analysis, quality control, storage, and presentation (Chapman, 2005). It is closely related to their potential use and ability to meet user needs (English, 1999), which Krol (2008) calls “use aptitude”.



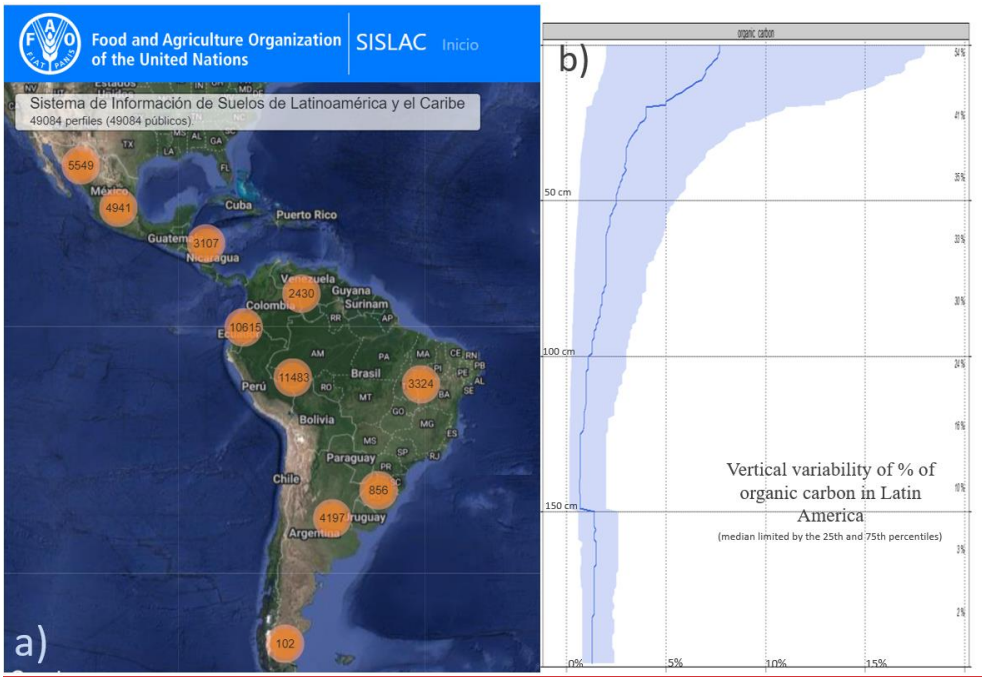


Figure 1: a) SISLAC interface, each number in the orange circles indicates the number of profiles in that area (from SISLAC webpage); b) ~~Location of the data usability demonstration area (ESRI 2022); c)~~ Vertical variability of the percentage of organic carbon in Latin America.

Con formato: Inglés (Reino Unido)

Con formato: Inglés (Reino Unido)

Con formato: Descripción, Espacio Después: 0 pto

Con formato: Inglés (Reino Unido)

Therefore, this research aims to~~: (i)~~ evaluate the quality of ~~the~~ SISLAC data and existing soil databases in terms of logical consistency~~; (ii) enhanced database improve the quality of the data~~ to ~~provide~~generate a new ~~updated~~ version~~; and (iii) demonstrate the usability, applicability, and potential~~ of the SISLAC database that meets the minimum requirements of ~~SISLAC to support digital soil mapping and soil-related policy research~~completeness in ~~South America by assessing the vertical and horizontal variability~~the description of ~~SOC percentage (as in Fig. 1c) in a region of Valle del Cauca Colombia. Two factors were considered for selecting the case study zone: (i) to be an area of agricultural production; and (ii) to have a relatively high density of soil profiles with SOC values~~profile horizons.

2 Data and Methods

The flow diagram (Fig. 2) shows the work carried out, consisting of four phases: the first comprises a revision of the special correspondence, the second an identification of spatially duplicated profiles, the third a validation of errors in the description of horizons and the fourth a correction of minor inconsistencies.

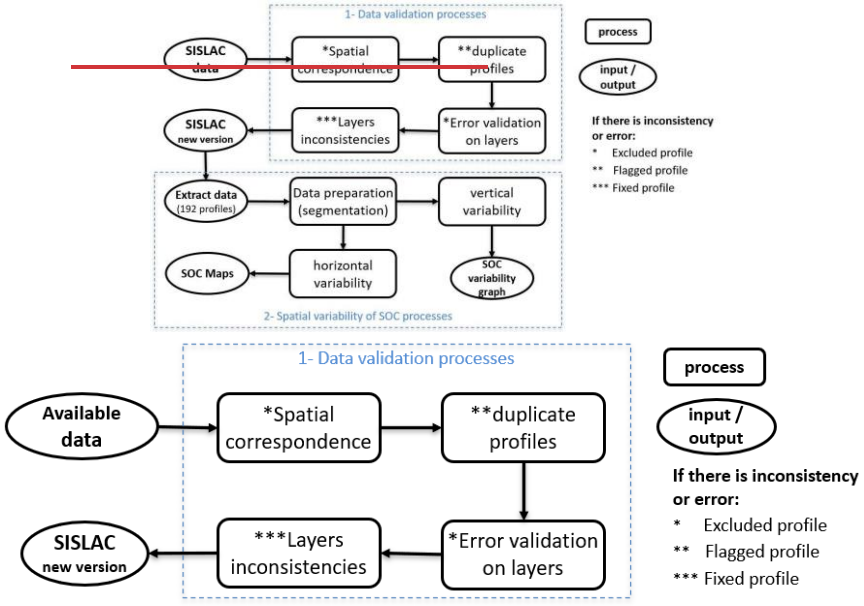


Figure 2~~.~~: Flowchart of this research. The blue box shows the validation processes applied to 100% of the data. ~~**The second part (lower frame) is about data preparation and estimation of the spatial variability of the SOC.**~~

2.1 Study area

The study area (Fig. 1a) is composed of the Latin American and Caribbean countries listed in Table 1, where since 2016 we have a soil database representative of such a diverse region. In the same figure, the number of profiles per region can be seen aggregated in orange circles. ~~In addition, an agricultural area located in the department of Valle del Cauca, Colombia (Fig 2a), was selected as case study zone to demonstrate usability. This area is located between latitudes 3°15' and 3°51' N and longitudes 75°57' and 76°10' W. The altitude of the area varies between 900 and 1,000 meters above sea level, and it has an approximate area of 1,437 square kilometers.~~

2.2 Data

The SISLAC database, which can be downloaded from the official site (http://54.229.242.119/sislac/es), consists of 49,084 profiles (with a total of 139,746 horizons). The number of these by country is detailed in Table 1. ~~For the first part of this research, 100% of the data were analyzed, while for the analysis of the spatial variability of the SOC, 192 profiles corresponding to the case study zone were used and their distribution is shown in Fig. 1b.~~Validations will be applied to 100% of the data.

Table 1.: Initial profiles and their layers by country. The countries are ordered by number of profiles, those with less than 100 profiles were grouped together. NA: Not Applicable.

Comentado [Diaz1]: RC1-09

Country	Profiles	Layers
Ecuador	13056	36749
México	12223	26051
Brazil	7842	23926
Colombia	4864	18900
Argentina	3774	16902
Paraguay	2830	6041
Bolivia	2557	2773
Venezuela	1056	4108
Uruguay	272	1382
Peru	148	631
Jamaica, Costa Rica, Cuba.	Between 100 and 51	NA
Chile, Guyana, Puerto Rico, Surinam, Nicaragua.	Between 50 and 26	NA
Panamá, Guatemala, Belice, Honduras, El Salvador, French Guiana, The Antilles, Barbados, Virgin islands, Trinidad y Tobago, República Dominicana.	Less than 26	NA
Total	49084	139746

Profile attributes are detailed in Table 2, in this the name of the attribute is listed in the first column, description in the second and data type in the third. The location is given in geographic coordinates, WGS84 datum. While for horizons and layers, their attributes are listed in Table 3 in the same way as in the profiles.

Table 2.: Profiles attributes, attributes related to the site description.

Column name	Description	Type
profile_identifier	Profile identifier	text
latitude	Profile latitude. Decimal degrees	numeric
longitude	Profile longitude. Decimal degrees	numeric
country_code	Country code. ISO 3166-1	text

date	Survey date	YYYY-MM-DD
source	data source	text
contact	Contact e-mail about the data	text
order	Soil order	text
type	Type (profile, auger)	text
license	License code ~~(~~; Public Domain Dedication and License: PDDL~~,~~; Attribution License: ODC-By~~,~~; Open Database License: ODC-ODbL~~,~~; Creative Commons Attribution 4.0 International: CC-BY~~,~~; Creative Commons Attribution - Non-Commercial 4.0 International: CC-BY-NC~~,~~; Creative Commons Attribution - Non Commercial No Derivatives 4.0 International: CC-BY-NC-ND~~).~~	text

Comentado [Diaz2]: RC1-10

Table 3~~.~~: Layers attributes, the measured attributes are numerical attributes (excluding top and bottom, which are the limits of each layer), in the last column, for each attribute measured, the percentage of records with valid data is indicated. NA: Not applicable.

Column name	Description	Units	% of layers with data
profile_identifier	Profile identifier	text	NA
layer_identifier	Unique ID of each horizon	text	NA
designation	Layer nomenclature	text	NA
top	Upper limit	numeric	NA
bottom	Lower limit	numeric	NA
bulk_density	Bulk density	numeric	15.2
ca_co3	Inorganic carbon (%)	numeric	5.7
coarse_fragments	Coarse fragments (%)	numeric	5.3
ecec	Effective cation exchange capacity	numeric	39.5
conductivity	Electric conductivity	numeric	23.6
organic_carbon	Organic carbon (%)	numeric	57.1
ph	pH specified with metadata	numeric	75.8
clay	Clay (%)	numeric	75.2
silt	Silt (%)	numeric	59.7
sand	Sand (%)	numeric	73.5
water_retention	Water retention (%)	numeric	3.1

The additional available databases are listed in Table 4, detailing the country, link to the data, number of profiles, license of use and spatial reference system. The data of the new version are in geographic coordinates, EPSG 4326, those in a different system will be reprojected. As with SISLAC data, 100% of the data is analyzed. The total number of profiles to be analyzed is 96783. These databases contain more or less attributes than those of the SISLAC structure, in this case, only those within the SISLAC structure will be processed.

Table 4: List of databases available for incorporation to the new version of SISLAC.

Country	Source	Number of Profiles	License to use	Spatial reference system (EPSG)
Argentina	http://sisinta.inta.gob.ar/	6180	No data	4326
Brazil	https://www.pedometria.org/febr/ctb0003/	400	Attribution 4.0 International (CC BY 4.0)	4326
Chile	https://doi.org/10.17605/OSF.IO/NMYS3	13612	Attribution 4.0 International (CC BY 4.0)	4326
Ecuador	https://doi.org/doi:10.6073/pasta/1560e803953c839e7aedef78ff7d3f6c	13542	Attribution 4.0 International (CC BY 4.0)	32717
México Series I y II	https://www.inegi.org.mx/app/biblioteca/ficha.html?upc=702825266707	13965	No data	6362

The above databases have different structures and attributes. Table 5 lists the SISLAC attributes found in those databases that will be added to this one. As can be seen, SOC is the common attribute in all, followed by clay, silt, sand and pH.

Table 5: SISLAC physical and chemical property attributes available in the databases. The attribute in common is SOC. The databases of Argentina, Ecuador and Mexico have the most attributes in common (Y = Yes; N= No).

	Bulk density	ca_co3	Coarse fragments	ecec	conductivity	Organic carbon	pH	clay	silt	sand	Water retention
Argentina	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Brazil	N	N	N	N	N	Y	N	Y	Y	Y	N
Chile	N	N	N	N	N	Y	N	N	N	N	N
Ecuador	Y	N	N	Y	Y	Y	Y	Y	Y	Y	N
México	N	N	N	Y	Y	Y	Y	Y	Y	Y	N

2.3 Methods

2.3.1 Quality assessment and improvement of SISLAC data

The evaluation of the quality and improvement of the ~~SISLAC~~ data were carried out in three stages, the first two for the site data and the third for the different layers. The first stage consisted of checking that the profiles are in the correct location (spatial correspondence). It was carried out by spatial intersection between the profiles (points) and the cartography of the countries (polygons). Based on the *country_code* attribute of the profiles, this correspondence was verified, those that coincided with their respective country were considered valid (Fig. 3a). Those that did not coincide were verified one by one, those that were within the limits of their country, considering the cartographic scale of the reference information, the precision

of the equipment with which the coordinate was taken, or the reference systems under which original data were taken, they were considered valid (Fig. 3b). Still, others had the coordinates inverted (Fig. 3c), the latitude and longitude values were exchanged, and their correspondence was verified again. Finally, the profiles outside their zone that could not be corrected for having the wrong location were excluded (Fig. 3d).

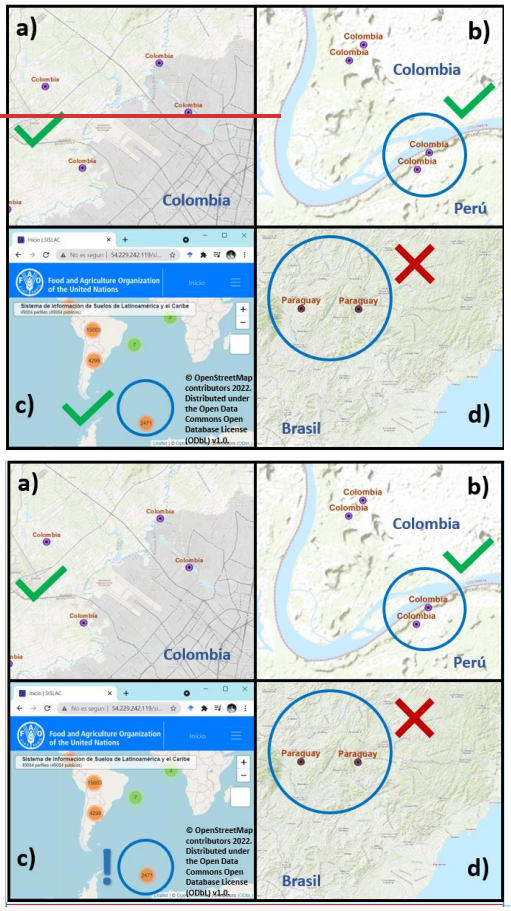


Figure 3.: Example of criteria found in spatial validation, (figures a, b and d source ESRI 2022; c: SISLAC webpage).

Comentado [Diaz3]: RC1-02

The second stage consisted of verifying if there are overlapping profiles, in addition, to verifying if the values in their attributes are different. For this, the number of times the same pair of coordinates is repeated was massively validated. Unlike the previous validation, these cannot be arbitrarily excluded since the correct profile cannot be determined. Then, those with duplicity were marked, so the user of the data can use the ones he considers appropriate. A new attribute in the profiles (*perfil_duplicado* of binary type) indicates if the profile has duplicity (TRUE) or is unique (FALSE). With respect to the additional databases, the existence of these profiles in SISLAC is also verified. If this occurs, the profiles with the highest number of valid attributes will be validated in order to keep them in the new database.

The third stage consisted of validating the description of the horizons or layers of each profile, verifying: $u_1 < v_1 \leq u_2 < v_2 \leq \ldots \leq u_n < v_n$; where u is the upper limit and v the lower limit. The upper limit must be less than its lower limit, and the lower limit must be less than or equal to the upper limit of the next layer. Gaps may exist but never overlap between layers. Gaps can occur for reasons such as: the data was not taken at the site, loss of data in the office, or error or omission in transcription. Errors were first validated, those in which the structure could not be corrected, so the profiles were excluded. Table 6 lists the three applied rules, their description, and an example of these.

Comentado [Diaz4]: RC1-03

Table 6: Layer errors validation. In the example, the layers with errors are highlighted in bold letters, for the first and third case, the last layers of the profiles are the ones with error, while in the second case, both layers have error because the limits have no data.

Validation	Description	Example
Duplicated layers	Layer limits are duplicated, and the values of the attributes are different.	ID Perfil / ID Horizonte / Top / Bottom / SOC % 176583 / 846371 / 0 / 10 / 32.4 176583 / 846371 / 10 / 23 / 26.1 **176583 / 846371 / 23 / 30 / 27.3** **176583 / 846371 / 23 / 30 / 2.1**
Empty limits	Upper and lower limits do not contain data.	ID Perfil / ID Horizonte / Top / Bottom / SOC % **Santa Rosa / Santa Rosa-1 / / / 1.22** **Santa Rosa / Santa Rosa-2 / / / 0.68**
Layers overlap	Layers overlap in a profile.	ID Perfil / ID Horizonte / Top / Bottom / SOC % SD-107050 / SD-107050-1 / 0 / 5 / 1.14 SD-107050 / SD-107050-2 / 5 / 20 / 0 SD-107050 / SD-107050-3 / 20 / 60 / 0.43 **SD-107050 / SD-107050-4 / 60 / 90 / 0** **SD-107050 / SD-107050-5 / 40 / 130 / 0** **SD-107050 / SD-107050-6 / 130 / 150 / 0**

After excluding the profiles with errors, the existence of inconsistencies was validated. Unlike errors, these can be corrected by guidelines that do not alter the structure of the profile. Next, Table 7 lists the rules applied to their description and the guideline for their correction. For a better understanding of the content of Table 7, Table 8 below illustrates the described inconsistency (middle column) and how it was corrected (third column).

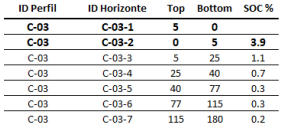
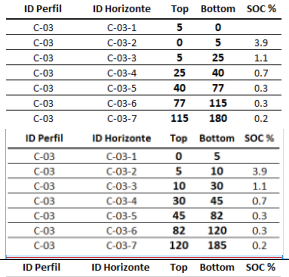
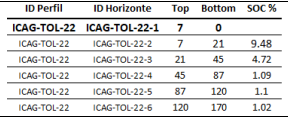
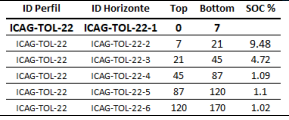
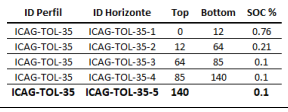
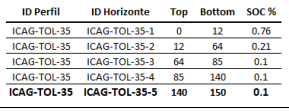
Table 7: Description of the validation of inconsistencies and their correction guideline.

Validation	Description	Correction Guideline

Organic layer	When the first layer is described in the opposite direction and from the second the normal description begins. Layer commonly known as organic.	Invert the values of the first layer and rescale subsequent limits based on the thickness of the organic layer.
Inverted layer	The value of the limits of a layer is inverted, it is verified considering also the previous and later layers.	Invert the values of the layer.
Continuous final layer	The value of the lower limit of the last layer is empty	Assign the value of the upper limit of the last layer plus 10. Defined by expert judgment to guarantee a minimum thickness in these layers
duplicated layer	Horizon that presents duplicate layers in all its attributes.	Delete duplicated layers.
Upper limit is null	The upper limit of a layer is null, in addition, the lower limit of that layer and the previous one is not null.	Assign the lower limit value of the previous layer.
Lower limit is null	The lower limit of a layer is null, in addition, the upper limit of that layer and the next are not null. The last layer is not validated.	Assign the value of the upper limit of the next layer.

Comentado [Diaz5]: RC1-12

Table 8: Illustration of inconsistencies and their correction guideline. In the second column in bold type the layers with inconsistency are shown, in the third column also in bold type it is shown how to correct them using the established guidelines. In the first case all profile limits are modified, for the rest only those of the layer with inconsistency.

Validation	Inconsistency	Correction Guideline
Organic layer		
Inverted layer		
Continuous final layer		

Comentado [Diaz6]: RC1-13

Duplicated layer		

ID Perfil	ID Horizonte	Top	Bottom	SOC %
176583	846371	0	10	32.4
176583	846372	10	23	26.1
176583	**846373**	**23**	**30**	**27.3**
176583	**846374**	**23**	**30**	**27.3**

ID Perfil	ID Horizonte	Top	Bottom	SOC %
176583	846371	0	10	32.4
176583	846372	10	23	26.1
176583	**846373**	**23**	**30**	**27.3**

Upper limit is null	

ID Perfil	ID Horizonte	Top	Bottom	SOC %
ICAG-VAC-C1	ICAG-VAC-C1-H1	0	12	8.52
ICAG-VAC-C1	ICAG-VAC-C1-H2	12	38	2.66
ICAG-VAC-C1	ICAG-VAC-C1-H3	38	68	1.06
ICAG-VAC-C1	**ICAG-VAC-C1-H4**		**90**	**0.84**
ICAG-VAC-C1	ICAG-VAC-C1-H5	90	150	0.55

ID Perfil	ID Horizonte	Top	Bottom	SOC %
ICAG-VAC-C1	ICAG-VAC-C1-H1	0	12	8.52
ICAG-VAC-C1	ICAG-VAC-C1-H2	12	38	2.66
ICAG-VAC-C1	ICAG-VAC-C1-H3	38	68	1.06
ICAG-VAC-C1	**ICAG-VAC-C1-H4**	**68**	**90**	**0.84**
ICAG-VAC-C1	ICAG-VAC-C1-H5	90	150	0.55

Lower limit is null	

ID Perfil	ID Horizonte	Top	Bottom	SOC %
Perfil 48081	**0**	**0**		**4.72**
Perfil 48081	**18**	**18**		**1.09**
Perfil 48081	**37**	**37**		**1.1**
Perfil 48081	**70**	**70**		**1.02**

ID Perfil	ID Horizonte	Top	Bottom	SOC %
Perfil 48081	**0**	**0**	**18**	**4.72**
Perfil 48081	**18**	**18**	**37**	**1.09**
Perfil 48081	**37**	**37**	**70**	**1.1**
Perfil 48081	**70**	**70**		**1.02**

2.3.2 Brief characterization of LAC soils using the new SISLAC database.

After applying the ~~above validations,~~ workflow presented in this research, we obtained a new harmonized database for Latin America ~~is obtained from~~ of soil profiles that ~~have~~meet minimum integrity requirements~~. The following is an exercise to demonstrate the usability of this database, taking~~ for use in different applications such as soil ~~organic carbon in percentage as a target variable and digital~~characterization, soil ~~mapping as a practical approach.~~

~~### 2.3.2 Data Usability~~

~~As mentioned in the introduction, the case study zone was selected for its availability of profiles, however, this exercise can be replicated by applying small changes to the code, which is available as part of this work. It should be considered that the chosen area should preferably be homogeneous and have a good density of profiles. The above is intended to demonstrate the potential of this database.~~

~~With the 192 profiles corresponding to the case study zone, the vertical and horizontal variability of the SOC was estimated. For the latter, the spatial resolution was 250 meters at three depth intervals: 0 to 5, 5 to 15 and 15 to 30 cm, following the standards of the project GlobalSoilMap (2015). As a first step, to harmonize the profiles — using the R software (R Core Team, 2018) — these were segmented using the *slice* function of the *aqp* library (Beaudette et al., 2013), which generates so many one-centimeter segments thick as the maximum depth of each profile. However, the values for each segment are inherited from the corresponding horizon, which generates a discontinuous or staggered representation that does not correspond to reality (Malone et al., 2017). To make their values more representative, they were adjusted using the equal area spline proposed by Bishop, et al. (1999) and available (*ea_spline* function) in the *ithir* library (Malone et al., 2009). An example is shown in Fig. 4 of the original profiles (a), their segmentation (b) and their adjusted values (c).~~evaluation, soil process recognition, and soil impact identification in the ecosystems. At last, in this research, we present a brief characterization of LAC soils through a principal components analysis (PCA).

Con formato: Espacio Antes: 12 pto, Después: 12 pto

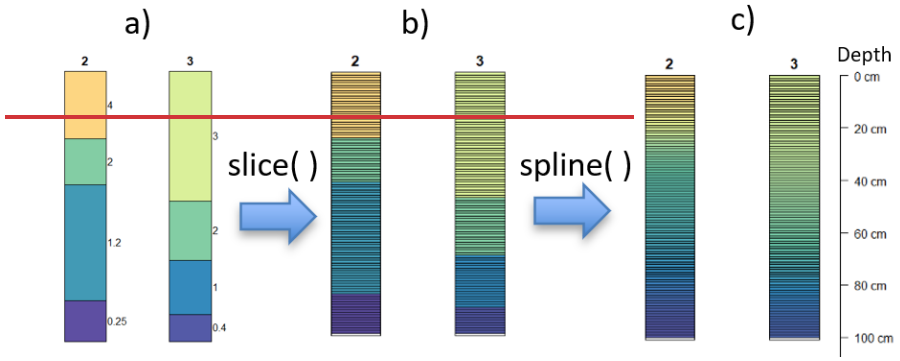


Figure 4, Harmonization of soil profiles, a) normal representation of the horizons and their SOC percentage; b) segmented horizons, in these the SOC percentage value (the same as the previous one) and c) horizons segmented and with adjusted values to improve their representation using the equal areas spline.

To calculate vertical variability, the aggregation function of the AQP package was used, which generates statistics for each depth segment (quantiles 5, 25, 50, 75, 95 and percentage of profiles used). From the data generated it is possible to know the behavior of continuous soil characteristics as a function of depth. On the other hand, ordinary kriging (OK) was used for horizontal variability assessment, a method frequently used to predict SOC (Bhunia et al., 2018; Duan et al., 2020; Yao et al., 2019; Y. Zhang et al., 2020; Z. Zhang et al., 2020). For each of the three intervals, the SOC percentage value of each profile corresponds to the average of the range of the previously adjusted and segmented values. First, the variogram was generated for each depth and fitted to a theoretical model to obtain the optimal values for interpolation. The estimation of values was carried out and the resulting information was classified according to three categories established by the *Instituto Geográfico Agustín Codazzi* (2016): low: less than 1.2%; medium: between 1.2% and 2.4%; high: greater than 2.4%. Finally, leave-one-out cross-validation was used for validating the performance of the OK and the root mean squared error (RMSE) and the coefficient of determination (R^2) indices were calculated. The Eq. (1) and (2) respectively used for the indices described are the following:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}(p_i - o_i)^2\right]^{1/2} \quad (1)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(p_i - o_i)^2}{\sum_{i=1}^{n}(o_i - \bar{o}_i)^2} \quad (2)$$

where o_i represents the observed values, p_i the values estimated and n is the number of locations used for the prediction.

~~3 Results~~

The PCA included profile characteristics (soil variables), profile depth, number of profile horizons, and profile classification according to the World Reference Base for Soil Resources WRB (IUSS Working Group WRB. 2007). The soil variables used were effective cation exchange capacity (ecec), pH, organic carbon (OC), and clay and sand content. These variables were selected because they are those with the highest number of records in the database. To represent the soil profile at each site, using the values registered by the horizon, the mean, minimum (min), and maximum (max) of each variable were calculated. The profile depth was identified as the maximum value of each site's "bottom" variable. Finally, the profile classification was obtained from the most probable soil group layer of SoilGrids at 250 meters of spatial resolution.

At last, 18 variables (17 quantitative and one qualitative) were included in the PCA. Those group soils with less than 100 profiles were removed from the dataset, and finally, a total of 27.960 soil profiles (those with complete cases) distributed in the LAC region were analyzed. The PCA was performed with the FactoMineR package in R (Lê et al., 2008).

3 Results

3.1 Quality assessment and improvement of SISLAC data

With the first validation, 2726 profiles were found that did not match their country. Table 9 lists these profiles at the country level. As can be seen, Bolivia has the largest number of these with 2,472 (90% of the cases). After the review, it was identified that 2471 of those cases (from Bolivia) had the coordinates inverted, so after changing the values and their validation, their correct location was verified, and they were considered valid. A total of 36 profiles (1.3% of those reviewed) were excluded for having an erroneous location, as presented in Fig. 3d, 3 from Colombia and 33 from Paraguay. A total of ~~49,048~~96,747 profiles (of the initial ~~49,084~~96,783 considering SISLAC and the additional databases) passed the second validation.

Table 9~~.~~: Spatial validation results, sorted by country with the highest number of inconsistencies (second column), the third column indicates how many profiles were excluded and the fourth column indicates how many were considered valid after being reviewed one by one.

Country	Inconsistent profiles	Excluded profiles	Valid profiles after check
Bolivia	2472	0	2472
Colombia	78	3	75
Paraguay	53	33	20
Ecuador	45	0	45
México	28	0	28
Brazil	16	0	16
Argentina	8	0	8
Nicaragua and Venezuela	5	0	5
Antillas	4	0	4

Peru and Uruguay	3	0	3
Chile and Costa Rica	2	0	2
Virgin Islands and Jamaica	1	0	1
Total profiles	**2726**	**36**	**2690**

With the second part of the validations, 1989 duplicate profiles were identified in SISLAC. Table 10 lists the country and the number of these. Brazil concentrates the largest amount with 1,680, 84.5% of the total and 21% of the total profiles provided by that country (with 7,842). As commented in the previous section, the profiles with duplicity were marked in the table, the profiles with duplicity in the *perfil_duplicado* field contain the value *TRUE*. In addition, profiles that already existed in SISLAC were excluded from the available databases. In Argentina 3374 of 6180; Ecuador 4633 of 13542 and in Mexico 7274 of 13965 profiles.

Table 10~~,~~: Profiles from SISLAC with spatial duplication by country.

Country	duplicated profiles
Brazil	1680
Argentina	94
Colombia	50
Jamaica	40
Venezuela	28
Uruguay	16
Surinam	11
Guatemala	9
Bolivia, Ecuador, Honduras, México	7
El Salvador, Guyana and Nicaragua.	6
Panamá	5
Costa Rica and Peru	4
Cuba	2
TOTAL	**1989**

Regarding the revision of the horizons from SISLAC, 7,380 errors were found (in 7,357 profiles). Table 11 details the number of these by country and type. Most were presented in Mexico, Paraguay and Brazil. Profiles with empty limits were the main error with 6,831 cases. Those 7,357 profiles were excluded for being inconsistent. On the other hand, in the additional data, 61 profiles from Argentina, 13 from Chile and 67 from Ecuador were found with overlapping horizons and 6493 profiles from Mexico with empty limits, so they were also excluded. An additional point was presented with the data from Mexico, the SISLAC data (12223 profiles) were the same as those of Series I and II (13965), the first ones had fewer attributes and an incorrect spatial location, for that reason all the data from Mexico were replaced by the valid profiles of Series I and II.

Table 11~~,~~: Layers error validation, ~~the~~only countries with errors are listed. The profiles with errors may be fewer than the errors per country because one profile may have more than one type of error.

Comentado [Diaz7]: RC1-08

Country	Duplicated layers	Empty limits	Layers overlap	Errors by country	Profiles with error
México	16	4942	32	4990	4990

Paraguay	0	1866	0	1866	1866
Brazil	35	12	339	386	368
Colombia	1	4	32	37	36
Ecuador	0	0	22	22	22
Argentina	4	2	12	18	18
Venezuela	1	4	10	15	13
Cuba	0	0	12	12	12
Costa Rica	1	0	9	9	8
Uruguay	3	0	5	8	7
Peru	0	0	6	6	6
Jamaica	0	0	4	4	4
Nicaragua	0	0	4	4	4
Chile	1	1	1	3	3
Errors by type	**62**	**6831**	**488**	**7380**	**7357**

Inconsistencies are described in Table 12. Most were found in Paraguay, Argentina and Colombia. The main causes were the null lower limit, continuous final horizon and duplicate horizon. All of these were corrected according to the established guidelines. Although 5474 inconsistencies were found, these correspond to 2215 profiles, so there were profiles with more than one inconsistency, for example, although in Paraguay there are 4066 inconsistencies, these are present in 931 profiles, the same number of profiles in that country.

Table 12~~.~~: Layers inconsistencies validation, in these, the bottom limit is null validation was the only one that did not present records with this inconsistency.

Country	Organic layer	Inverted layer	Continuous final layer	Duplicated layer	Lower limit is null	Inconsistencies by country.
Paraguay	0	0	931	0	3135	**4066**
Argentina	0	0	993	0	2	**995**
Colombia	38	5	0	339	0	**382**
Brazil	0	3	0	11	0	**14**
Venezuela	2	0	7	0	0	**9**
México	0	1	1	1	0	**3**
Uruguay	0	0	3	0	0	**3**
Bolivia	0	0	1	0	0	**1**
Jamaica	0	0	1	0	0	**1**
Total by type	**40**	**9**	**1937**	**351**	**3137**	**5474**

Finally, the following tables summarize the results obtained, first, Table 13 ~~shows a summary of the data after the validation and correcting processes. Only those~~ lists the countries ~~that had changes due to excluded profiles are listed. The second and third columns show the initial and valid profiles, respectively;~~ with a change in the ~~corresponding~~ number of ~~horizons is indicated in parentheses. The Errors column indicates the number of~~ profiles. As can be seen, there was an increase in the first 5 countries, since the available databases correspond to these countries, while in the following countries profiles were excluded

due to errors in ~~the~~ their description. In addition, Table 14 lists the sources of the data that contribute to this new version of SISLAC, as can be seen, there are almost 10,000 profiles obtained from WoSIS and the rest are contributed by institutions in the countries of the region. To conclude, Table 15 shows the initial and final percentage of records with valid values for the soil property attributes, showing that ~~country and inconsistencies is the number of inconsistencies found and corrected.~~SOC, pH, clay, silt and sand are the attributes with the highest percentage. From SISLAC, after the processes carried out, of the 49,084 initial profiles, 15% of these were excluded and another 4.5% were corrected so that they met the minimum integrity requirements, ~~data.~~ in addition, 17% of the profiles in the other databases already existed in SISLAC. Of the 9,6783 total profiles analyzed, 32% were excluded due to erroneous description or because they already existed in the SISLAC data. The revised version consists of ~~41,691~~66,746 profiles made up of ~~129,355~~192,568 horizons and layers.

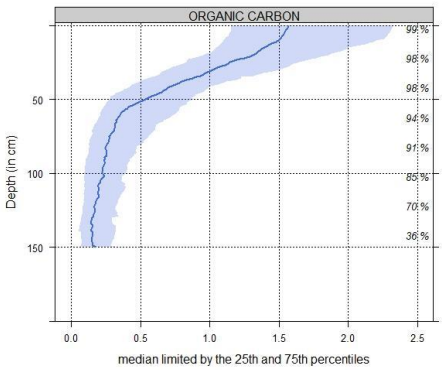
Table 13~~.~~: Details of the SISLAC data validation processes, total number of layers are in parentheses, the errors caused the profile to be excluded, while the inconsistencies were corrected.

Country	Initial profiles (layers)	Remain profiles (layers)	Errors	Inconsistencies
Ecuador	13056 (36749)	~~13034 (36582~~21912 (70204)	22	0
Chile	45 (220)	~~42 (201~~13403 (16371)	3	0
Brazil	7842 (23926)	~~7474 (226168~~114 (23367)	368	14
México	12223 (26051)	~~7233 (209137~~472 (23899)	4990	3
Argentina	3774 (16902)	~~3756 (168136~~515 (30041)	18	995
Colombia	4864 (18900)	4825 (17615)	39	382
Paraguay	2830 (6041)	931 (4066)	1899	4066
Venezuela	1056 (4108)	1043 (4051)	13	9
Uruguay	272 (1382)	265 (1321)	7	3
Peru	148 (631)	142 (561)	6	0
Jamaica	76 (361)	72 (331)	4	1
Costa Rica	55 (318)	47 (257)	8	0

Cuba	52 (282)	40 (186)	12	0
Nicaragua	26 (132)	22 (99)	4	0

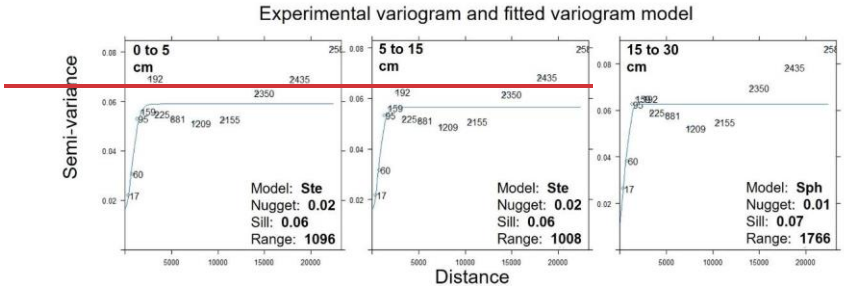
~~3.2 Data Usability~~

~~With the 192 profiles processed which did not present errors or inconsistencies in the validation process, using the aggregation function of the *aqp* library, the SOC vertical variation is shown in Fig. 5, the blue line corresponds to the median, while the shading around it corresponds to at the 25th and 75th percentiles, that is, the variability of 50% of the SOC data. As can be seen, from 0 to 50 cm depth, the median values varies from 1.6% to 0,5%, respectively. While the variability of 50% of the data for the same interval ranges from 0.3% in the minimum values to 2.3% in the maximum values. After 50 cm of depth, the values stabilize, with a median value of 0.5% to 0.3% and almost constant variation up to 150 cm.of depth.~~

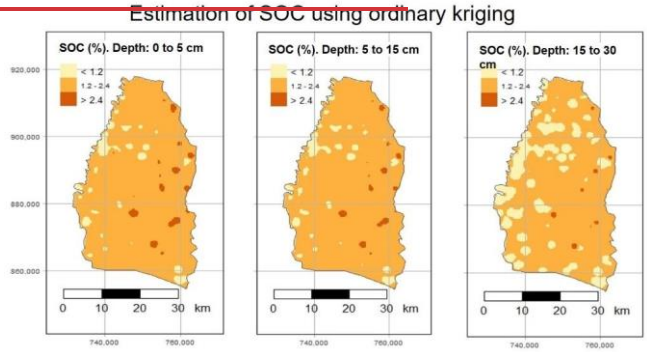


~~**Figure 5, Vertical variability of the SOC in the area of interest**~~

~~Semivariograms obtained allowed us to know the spatial behavior of the profiles. Figure 6 shows that for the first two depths the resulting parameters were similar, while for the third one the range increases and the adjustment model is different. The resulting cartography is shown in Fig. 7, in which it is observed that the estimates have the same distribution patterns of the different categories, although in the third depth (15 to 30 cm) the spot of low category increases. Table 14 shows details of the area percentages for each depth interval and each category. It is observed that the medium category predominates in the three depths mapped with more than 80%, while the low category increases slightly with depth, the inverse being the case in the high category, which decreases.~~



~~Figure 6, Adjusted variograms for the three depths, the first two fit the same model (Stein parameterization), with similar range, nugget and sill values, while the third fit a spherical model, its range was considerably larger and the nugget and sill values are similar to the previous ones.~~



~~Figure 7, interpolation results for each depth, orange color predominates, which represents a medium SOC percentage content, as the depth increases the SOC percentage decreases and more yellow patches are observed, mainly in the western zone.~~

~~Table 14, Percentages of area by depth and category, the values for the 0 to 5 and 5 to 15 cm intervals show very similar percent areas, while the 15 to 30 interval shows what was observed in Fig. 7, that the percent SOC decreases.~~

Table 14: Count of profiles contributed by each data source to the new version of SISLAC.

Source	Country	Profiles
CHLSOC: the Chilean Soil Organic Carbon database	Chile	13359
WoSIS July 2016 Snapshot	Various	9230
Harmonized soil database of Ecuador (HESD)	Ecuador	8842
SIGTIERRAS-MAG	Ecuador	8342
SISINTA (sisinta.inta.gob.ar)	Argentina	6277

Instituto Geográfico Agustín Codazzi	Colombia	4687			
MAGAP & IEE	Ecuador	4633			
México Serie-II	México	4420			
México Serie-I	México	3052			
ZONISIG	Bolivia	2145			
Reservatorio do DNOS-CORSAN	Brazil	400			
Sistema de información de suelos de la depresión del lago de Valencia - SISDELAV	Venezuela	366			
Sistema Integrado de Apoyo al Productor - SIAP	Venezuela	270			
ECOSUR-VT-2016	Bolivia	242			
N/D	Various	183			
Ministerio de Ganadería, Agricultura y Pesca	Uruguay	141			
Universidad Central de Venezuela - UCV	Venezuela	43			
Instituto Nacional de Investigaciones Agrícolas - INIA	Venezuela	42			
SPECTROLAB	**Depth 1: 0- 5 cm**Bolivia	**Depth 2: 5 - 15 cm**	**Depth 3: 15 - 30 cm**		
% SOC low Centro Internacional de Agricultura Tropical - CIAT	5.2Bolivia	5.8	19		
% SOC medium Universidad Mayor De San Simon - UMSS	92.6Bolivia		92.614	80.4	
% SOC highZONISIG_GQ	2.2Bolivia		1.69	0.6	
Total of profiles			**66746**		

~~Finally, to evaluate the kriging performance, using leave-one-out cross-validation, the RMSE and R^2 indices were obtained. Fig. 8 shows the results of these indexes, as can be seen, the RMSE value was similar for the three intervals, 1.78% from 0 to 5 cm, 1.77% from 5 to 15 cm and 1.79% from 15 to 30 cm. While the resulting R^2 was 0.56, 0.53 and 0.83, respectively.~~

Celdas eliminadas

Con formato: Fuente: +Cuerpo (Times New Roman), Sin Negrita

Con formato: Izquierda

Tabla con formato

Con formato: Fuente: +Cuerpo (Times New Roman), Sin Negrita, Color de fuente: Negro, Inglés (Reino Unido)

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman), Sin Negrita

Con formato: Izquierda

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman), Color de fuente: Negro, Inglés (Reino Unido)

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman), Español (México)

Celdas eliminadas

Con formato: Izquierda

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman), Español (México)

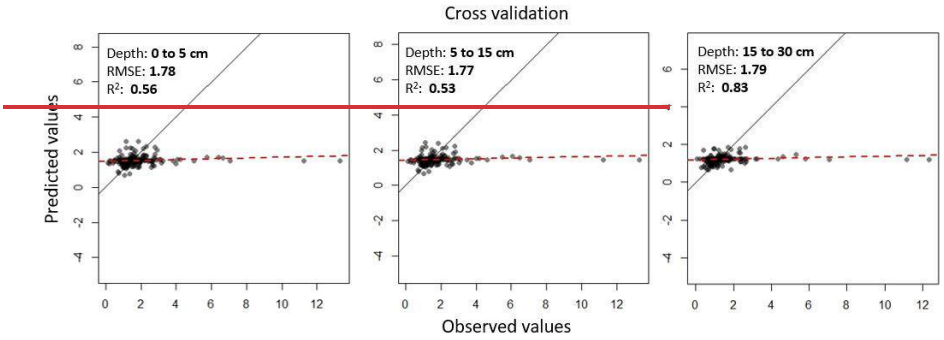
Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Fuente: +Cuerpo (Times New Roman)

Con formato: Izquierda

Comentado [Diaz8]: RC2-04



~~**Figure 8, Cross validation, some subestimated values are observed towards the right side of the graphs, the RMSE values are similar, while the R^2 for the last interval increases notably.**~~

Table 15: Percentage of valid records for soil properties, showing that SOC is the attribute with the highest number of valid records, followed by pH, clay, silt and sand.

Attribute	Initial percentage of valid values	final percentage of valid values
Bulk density	15.2	13.6
Inorganic carbon (%)	5.7	5.5
Coarse fragments (%)	5.3	6.8
Effective cation exchange capacity	39.5	51.9
Electric conductivity	23.6	18.2
Organic carbon (%)	57.1	65.2
pH	75.8	66.0
Clay (%)	75.2	66.1
Silt (%)	59.7	55.4
Sand (%)	73.5	64.9
Water retention (%)	3.1	2.6

3.2 Brief characterization of LAC soils using the new SISLAC database.

According to the most probable soil group from SoilGrids 2.0 (based on the World Reference Base - WRB of 2006), the 27.960 soil profiles (those with complete cases) in the new SISLAC database correspond to 16 soil Groups. The Cambisols (22.2%), Andosols (19.9%), and Ferrasols (14.6%) are those with the major amount of soil profiles. Cambisols are across all LAC regions, principally in Colombia, Ecuador, Mexico, Venezuela, Brazil, and Argentina. Andosols are primarily in the Andes

Mountains regions (Colombia and Ecuador) and some volcanic mountains in Mexico and Costa Rica. Ferralsols are principally from South American regions in Brazil, Ecuador, Colombia, and Argentina. Meanwhile, Arenosols (0.5%), Planosols (0.7%), and Fluvisols (1%) are those less represented in the database. Arenosols are principally in the northern region of Mexico and central Brazil. Planosols are in the south of Brazil and North of Argentina. Fluvisols are principally in the north of Colombia, East of Brazil, and west of Ecuador.

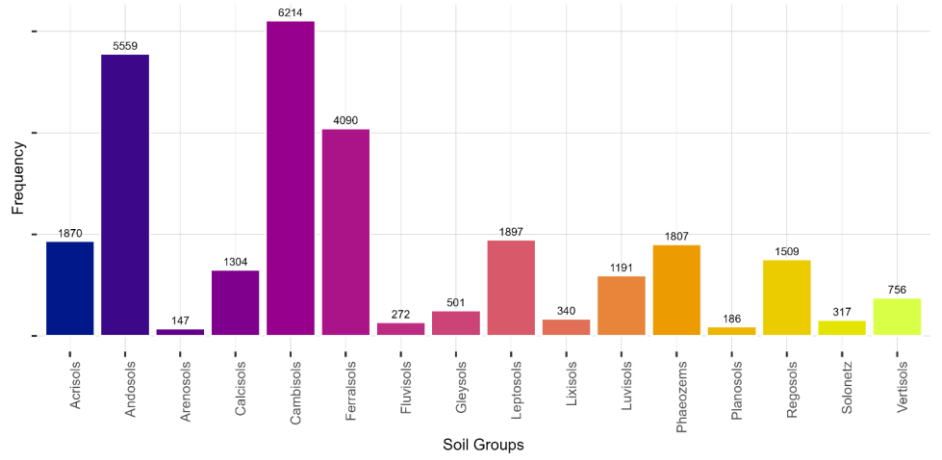


Figure 5. Frequency of soil profiles by Soil Group according to the World Reference Base (WRB).

In the PCA, five dimensions have eigenvalues greater than 1 (Table 16). These first five dimensions explained 86.49% of the total variance in the dataset. The first two dimensions express 52.52% of the total variance, which means that 52.52% of the individuals' (or variables') total cloud variability is explained by the plane formed by Dim 1 and Dim 2. The first dimension (28.73% of variance explained) represents soil texture (clay and sand content) and the cation exchange capacity variables (Figure 6A). On the other hand, the second dimension (23.79% of variance explained) captures the variability of pH, organic carbon, and cation exchange capacity (Figure 6A). The third dimension (16.28% of variance explained) comprises profile depth, number of profile horizons, and cation exchange capacity (Figure 6B). The organic carbon content and pH variables represent the fourth dimension (9.72% of variance explained) (Figure 6B).

Table 16. Decomposition of the total inertia obtained from the principal component analysis based on profile characteristics of 28.460 sites of the new version of the SISLAC database.

Variable	Dim 1	Dim 2	Dim 3	Dim 4	Dim 5
Eigenvalue	4.88	4.04	2.77	1.65	1.36
Explained variance (%)	28.73	23.79	16.28	9.72	7.98
Cumulative variance (%)	28.73	52.52	68.79	78.51	86.50

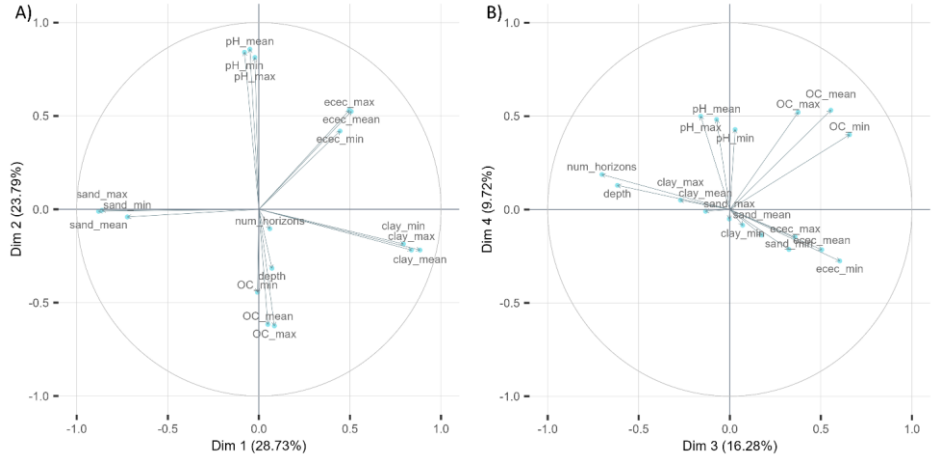


Figure 6: Variables map for the first plane. Quantitative variables such as pH, effective cation exchange capacity (ecec), organic carbon (OC), clay and sand content, number of horizons (num_horizons), and profile depth (depth).

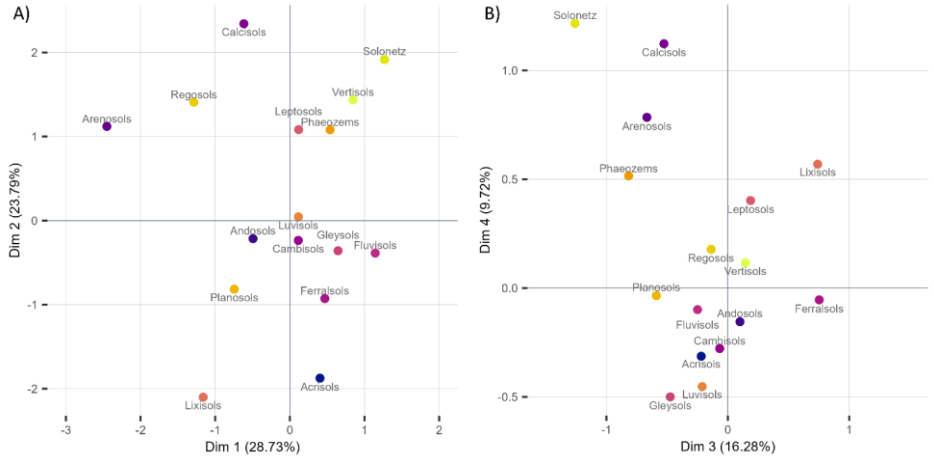


Figure 7: Quality factor map with soil group according to the World Reference Base (WRB). A) First plane and B) Second plane of the principal component analysis.

The qualitative factor map shows the distance between soil groups in the first plane (Figure 6). In the first plane, the soil groups most differentiated from others are Arenosols, Calcisols, Solonetz, Acrisols, and Lixisols (Figure 7A). The Arenosols are those most correlated with Dim 1, representing the soil's texture and cation exchange capacity. Meanwhile, Calcisols, Lixisols, Solonetz, and Acrisols are most correlated with Dim 2, which represents the soil's pH and organic carbon. On the other hand, in the second plane, the soil groups most differentiated are Solonetz, Calcisols, Phazoems, Lixisols, Ferrasols, and Gleysols (Figure 7B). The Solonetz, Phaeozems, Ferrasols, and Lixisols are most correlated to Dim 3, which represents profile attributes such as profile depth and number of horizons; meanwhile, Solonetz, Calcisols, and Arenosols are most correlated with Dim 4, which represents principally organic carbon content and pH of the soil.

4 Discussion

This work made it possible to identify that the main problems in the SISLAC profiles occur systematically in some countries. In addition, ~~it shows the potential of improved soil databases for the generation of spatial information such as SOC or any~~

~~other property which have been surveyed~~we were able to incorporate new data to improve this database and make available to the soil community a greater number of soil profiles of the region.

4.1 Quality assessment and improvement of SISLAC data

As shown in Table 1, the most frequent error in the profiles was due to empty limits, which occur mainly in Mexico and Paraguay with 67% and 25% of the total errors, respectively. In Mexico, these errors correspond to 40% of the profiles provided, while in Paraguay to 65%. On the other hand, most of the inconsistencies (Table 12) are found in Argentina, Paraguay and Colombia with 44%, 42% and 12% of the total respectively. Although all these inconsistencies were corrected, it is observed that, for example, in Paraguay of the total profiles provided (2830), only 9 contain SOC values, the rest have all the empty attributes. The foregoing represents a limitation if one wanted to carry out any type of analysis with these data.

The validations were defined by expert judgment, they coincide with those described in the works of Batjes (1995) and Leenaars (2013) and were applied to all the elements. For the horizons, it was guaranteed that they were correctly described, since as these authors indicate, if they are not adequately described, in-depth analyzes cannot be carried out since the analysis tools may fail or a high degree of uncertainty may be generated.~~6~~

~~The variability allowed knowing the behavior of the SOC in its vertical and horizontal dimensions, the latter following standards for the elaboration of spatial information on soil properties such as those of GlobalSoilMap. An important aspect is that with the segmentation and adjustment of the values carried out, it is possible to generate information for any interval, or even for each centimeter of depth.~~

~~This work is a effort towards the consolidation and availability of more and better data in the region, which should be reflected in national results such as those of Araujo-Carrillo et al. (2021) and~~ Varón-Ramírez et al. (2022~~) in Colombia; Armas et al. (2022) in Ecuador; Pfeiffer et al. (2020) in Chile or Schulz et al. (2022) in Argentina.~~ ~~Free access to these data can increase the knowledge of the properties or improve the existing one. It can also generate information with global standards, under which the cartography presented in this research was elaborated.~~ ~~From this mapping it is observed that the values obtained for the RMSE and R^2 index (Fig. 9) for the range of 0 to 5 cm were 1.78% and 0.56 respectively. From 5 to 15 were 1.77% and 0.53 and from 15 to 30, 1.79% and 0.83, very similar results in the first two intervals, partly due to the dimensionality and proximity between them. Taking as reference the R^2 values, all higher than 0.5, this work presents better results than similar works that used the same method for SOC estimation, for example, those reported by Y. Zhang (2020), using 122 samples in an area of 7692 km², those of Xin et al. (2016) with 180 samples in 72 km² or those of Yao (2019) using 90 samples, which obtained R^2 values of 0.21, 0.2 and 0.4 respectively.~~

In the profiles of the available databases, the data had a correct description of the profiles, so most of them are incorporated into SISLAC. In these, the main attributes available were SOC, pH, clay, silt and sand. With these data, an increase in the database of more than 50 percent was achieved, since the revised SISLAC database had just over 42,000 records and the new version exceeds 66,000 soil profiles from the entire Latin American region.

Comentado [Diaz9]: RC1-07

Comentado [Diaz10]: RC2-08

Comentado [Diaz11]: RC1-05

4.2 Brief characterization of LAC soils using the new SISLAC database.

A principal components analysis (PCA) considering the profile attributes and soil variables with the highest number of records (SOC, pH, ecec, and clay and sand content, number of horizons and profile depth) was carried out to characterize the new SISLAC database. A way to validate the database information was to relate those profile attributes and soil variables with a soil classification. In the database, just 37% of the soil profiles have a taxonomic classification, 26% based on USDA (Profiles in Argentina, Colombia and Ecuador, principally) and 11% based on WRB (Profiles in Mexico) taxonomic classification system. Therefore, it was necessary to identify the most probable soil group from a unified global source (SoilGrids 2.0) for the 27,960 soil profiles with complete records for the soil variables included in the PCA. If it is not a field-based taxonomic classification of each soil profile, the SoilGrids product represents the global tendency of the world soils (Poggio et al., 2021). Some soil groups are separated from others and strongly correlated to dimension one or two according to soil variables. As expected, soil groups characterized by the variables included in the PCA are those most differentiated in the analysis. Soil groups characterized by textural attributes such as Arenosols (high content of sand) are strongly correlated with Dim 1, which represents the sand and clay content of the mineral soil. Meanwhile, soil groups characterized by accumulation of sales such as Calcisols (high content of calcium) or Solonetz (high content of exchangeable sodium) are correlated with Dim 2 due to the effect of sales in the pH of the soil; similarly, those soil groups with an accumulation of organic matter such as Phaezoems (dark superficial layers) are also mostly correlated with Dim 2, which represent organic matter characteristics too.

On the other hand, those majors represented soil groups in the new SISLAC database, and no characterized by the variables included in the PCA are not differentiated from other soil groups. Cambisols (which are identified by edafogenetic alteration evidence but not stronger alteration or accumulation processes), Andosols (which are identified by their relationship between Fe and Al, bulk density, and phosphate retention), and Ferralsols (which are identified by Fe or Mn accumulation in the soil profile) are those soil groups major represented in the database (57% of the total soil profiles). These soil groups appear at the central portion of the factor maps in the PCA and do not show a specific correlation with dimensions.

The PCA analysis showed the relation between soil variables in the new SISLAC database and soil groups (from a different source), making evident this new database's value and potential use. However, it is essential to highlight that this PCA was made with 42% (27,960) of the total soil profiles in the new SISLAC database (66,746). This analysis does not represent regions with few complete data such as, Central America (Guatemala, Honduras, Nicaragua, Cuba, Dominican Republic, among others) and South America (Chile, Peru, Bolivia, Paraguay and south of Venezuela and Brazil).

4.3 Limitations and future directions

A factor not considered in this work was the validation of the attributes of the horizon properties in a simple or combined way to identify outliers, for example, using Tukey's rule (Pham et al., 2019) or out of range (pH values less than 0 or greater than 14). This omission was due to the fact that a large part of the horizons did not have assigned values. As shown in Table 15, only four attributes (SOC, pH, clay and sand) exceed 65% of records with values, while another two (silt and Effective cation

Con formato: Color de fuente: Color personalizado(RGB(0;0;10))

exchange capacity) have just over 50% values. The other attributes do not exceed 20%, there are even three properties with less than 6%, which are inorganic carbon, coarse fragments and water retention. ~~The above was a factor that influenced the choice of the area for the case study, it is important to have data, but also that they are complete.~~

A possible reason why the profiles have been provided incomplete may be the one mentioned by Arrouays et al. (2017) or Rossiter (2004), about privacy or data ownership policies, in addition to institutional, legal and cultural factors, prevent data from being fully shared. Breaking down those barriers would allow that data to be used by a larger number of global users. Given the importance of these databases, it is pertinent to make new efforts to collect data from other sources, such as research centers or universities, in order to strengthen this or other databases. ~~As shown in the analysis of SOC variability, this~~This revised version of SISLAC data offers the potential to generate information that helps decision-making on issues in which soils are decisive. It can also be used to plan future soil surveys in areas with low density or where updated information is required. Another possible use of these data may be to improve existing information (in scale and depth), such as the Organic Carbon Map (FAO & ITPS, 2018), or to generate new information such as that presented by Gutierrez (2020) using SISLAC data.

In summary, from the total data set, 38% of profiles were excluded and another 4.5% were corrected and from the available databases, nearly 24,000 soil profiles were incorporated. This work tried to exclude as few profiles as possible given their importance in areas with low spatial density. Furthermore, as mentioned by Hengl (2019), this data is the only thing available at this time in many places, so its availability is important. Knowing the level of integrity of the data, what the main problems are and where they occur, can help the countries involved to know where to put more efforts to have more reliable data. In that sense, this work may contribute to support soil conservation efforts, increase food and water security, maintain healthy ecosystems, and reduce climate change's impact.

5 Data availability

The data is available at ~~https://doi.org/10.5281/zenodo.6540710~~https://doi.org/10.5281/zenodo.7876731 (Díaz-Guadarrama, S. & Guevara, M., ~~2022~~2023) in ~~three different formats:~~ Comma-Separated Values format (csv~~)., Microsoft Access Database (.mdb), and as PostgreSQL – PostGIS Database backup~~). The source code used for data processing is also available at the same repository.

6 Conclusions

This work was successful in improving the SISLAC database, thus generating a revised database version in which all the soil profiles have high quality and completeness to be efficiently used in multiple applications (e.g., digital soil carbon mapping and reporting). In the revised SISLAC database, 15% of soil profiles were excluded (e.g., horizon information duplicated or overlapped) and 4.5% of the soil profiles were adjusted to the same data structure. ~~We demonstrate the usability of the revised~~

~~SISLAC database developing a reproducible digital soil carbon mapping framework which improves the analysis of soil carbon and depth relationships from a discrete to a continuous fashion. In our usability example we observe relatively high accuracy (R^2 of 0.5 and RMSE 1.78), demonstrating the potential of databases such as SISLAC to generate information on the spatial variability of soils across large areas with high spatial detail. The database used~~With the available soil databases, it was possible to increase the database by more than 50 percent, initially the valid SISLAC profiles were around 41 thousand, so the additional profiles represent more than 25 thousand records. SISLAC is a product of the cooperation of national institutions of the countries of the region, investing efforts in the collection of additional data, for example, those produced in universities or research centers could lead to an increase in the volume of the revised version of SISLAC (as new and better data become available), and these in turn, may allow the generation of new spatial information on soil properties to improve what is currently available.

Competing interests

The authors declare that they have no conflict of interest.

Acknowledgements

Sergio Díaz acknowledges support by the Colombian Institute of Educational Credit and Technical Studies Abroad – ICETEX. Mario Guevara acknowledges support from grants: UNESCO-IGCP-IUGS, 2022 (#765), UNAM-PAPIIT, 2021 (#IA204522) and USDA-NIFA-AFRI, USA, 2019 (#2019-67022-29696).

We would also like to thank the people who contributed data to SISLAC from their institutions: Bolivia: Miguel Ángel Vaca; Chile: José Sergei Padarian Campusano; Colombia: Oscar Daniel Beltrán Rodríguez, Napoleón Ordoñez Delgado, Javier Otero García, Rafael Antonio Pedraza Rute and Reinaldo Sánchez López; Costa Rica: Bryan Alemán Montes; Ecuador: María Natalia Rumazo Chiriboga and Darwin Sánchez Rodríguez; El Salvador: Edgard Mayen; Guatemala: Juan Antonio Padilla Cruz and Claudia Cecilia Saput; Honduras: Arturo Varela Ocón; Nicaragua: Jose Ariel Cruz Martínez and Wilmer Rodríguez; Perú: Germán Belizario-Quispe, Marcos Gabriel Cerna Arellano, Alberto Cortez Farfán, José Carlos De la Cruz Espinoza, Gouri Agusto Aparicio Cavero, Gabriel Máximo Larota Cantuta, Efraín Oscar Rosario Sánchez, Kharolyn Elizabeth Santander Hidalgo Candia, Raúl Uscamayta Quispe and Jorge Vásquez Acuña; Uruguay: Inés Barilani, Gastón Bentancor, Gonzalo Daniel Pereira Facal and Claudio Prieto.

References

Amirinejad, A. A., Kamble, K., Aggarwal, P., Chakraborty, D., Pradhan, S., and Mittal, R. B.: Assessment and mapping of spatial variation of soil physical health in a farm. Geoderma, 160(3–4), 292–303.

https://doi.org/10.1016/j.geoderma.2010.09.021, 2011

Angelini, M., Rodriguez, D. M., Olmedo, G. F., and Schulz, G.: Sistema de Información de Suelos del INTA (SISINTA): presente y futuro, in XXVI Congreso Argentino de la Ciencia del Suelo, Tucumán, Argentina, 15–18 May 2018, 5 pp, https://www.researchgate.net/publication/325607030_Sistema_de_informacion_de_suelos_del_INTA_SISINTA_Presente_y_futuro, 2018

Araujo-Carrillo, G. A., Varón-Ramírez, V. M., Jaramillo-Barrios, C. I., Estupiñan-Casallas, J. M., Silva-Arero, E. A., Gómez-Latorre, D. A., and Martínez-Maldonado, F. E.: IRAKA: The first Colombian soil information system with digital soil mapping products. Catena, 196, 104940. https://doi.org/https://doi.org/10.1016/j.catena.2020.104940, 2021

Armas, D., Guevara, M., Alcaraz-Segura, D., Vargas, R., Soriano-Luna, Á., Durante, P., and Oyonarte, C: Digital map of the organic carbon profile in the soils of Andalusia, Spain. Ecosistemas, 26(3), 80–88. https://doi.org/10.7818/ecos.2017.26-3.10, 2017

Armas, D., Guevara M., Bezares F., Vargas R., Durante P., Osorio V.H., Jiménez W.A., and Oyonarte C.: Harmonized Soil Database of Ecuador 2021 ver 3. Environmental Data Initiative. https://doi.org/10.6073/pasta/1560e803953c839e7aedef78ff7d3f6c, 2022

Arrouays, D., Leenaars, J. G. B., Richer-de-forges, A. C., Adhikari, K., Ballabio, C., Greve, M., Grundy, M., Guerrero, E., Hempel, J., Hengl, T., Heuvelink, G., Batjes, N., Carvalho, E., Hartemink, A., Hewitt, A., Hong, S., Krasilnikov, P., Lagacherie, P., Lelyk, G., …, Rodriguez, D.: Soil legacy data rescue via GlobalSoilMap and other international and national initiatives. GeoResJ, 14, 1–19. https://doi.org/10.1016/j.grj.2017.06.001, 2017

Batjes, N.: World inventory of soil emission potentials -WISE 2.1, International Soil Reference and Information Centre, 65pp, https://www.isric.org/sites/default/files/ISRIC_TechPap26.pdf, last access: 6 September 2022, 1995

Batjes, N.: Harmonized soil property values for broad-scale modelling (WISE30sec) with estimates of global soil carbon stocks. Geoderma, 269, 61–68. https://doi.org/10.1016/j.geoderma.2016.01.034, 2016

Batjes, N., Ribeiro, E., Van Oostrum, A., Leenaars, J., Hengl, T., and Mendes De Jesus, J.: WoSIS: Providing standardised soil profile data for the world. Earth Syst Sci Data, 9(1), 14. https://doi.org/10.5194/essd-9-1-2017, 2017

Batjes, N., Ribeiro, E., and Van Oostrum, A.: Standardised soil profile data to support global mapping and modelling (WoSIS snapshot 2019). Earth Syst Sci Data, 12(1), 299–320. https://doi.org/10.5194/essd-12-299-2020, 2020

Beaudette, D., and O'Geen, A. T.: Soil-Web: An online soil survey for California, Arizona, and Nevada. Comput Geosci, 35(10), 2119–2128. https://doi.org/10.1016/j.cageo.2008.10.016, 2009

Beaudette, D., Roudier, P., and Geen, A. T. O.: Algorithms for quantitative pedology : A toolkit for soil scientists. Comput Geosci, 52, 258–268. https://doi.org/10.1016/j.cageo.2012.10.020, 2013

Bhunia, G. S., Shit, P. K., and Maiti, R.: Comparison of GIS-based interpolation methods for spatial distribution of soil organic carbon (SOC). Journal of the Saudi Society of Agricultural Sciences, 17(2), 114–126. https://doi.org/10.1016/j.jssas.2016.02.001, 2018

Bini, D., Santos, C. A. dos, Carmo, K. B. do, Kishino, N., Andrade, G., Zangaro, W., and Nogueira, M. A.: Effects of land use

on soil organic carbon and microbial processes associated with soil health in southern Brazil. Eur J Soil Biol, 55, 117–123. https://doi.org/10.1016/j.ejsobi.2012.12.010, 2013

Bishop, T. F. A., Mcbratney, A., and Laslett, G. M.: Modelling soil attribute depth functions with equal-area quadratic smoothing splines. Geoderma, 91(1), 27–45. https://doi.org/https://doi.org/10.1016/S0016-7061(99)00003-8, 1999

Bockheim, J. G., Gennadiyev, A. N., Hammer, R. D., and Tandarich, J. P.: Historical development of key concepts in pedology. Geoderma, 124, 23–36. https://doi.org/10.1016/j.geoderma.2004.03.004, 2005

Bouma, J., Broll, G., Crane, T., Dewitte, O., Gardi, C., Schulte, R., and Towers, W.: Soil information in support of policy making and awareness raising. Curr Opin Env Sust, 4(ii), 552–558. https://doi.org/10.1016/j.cosust.2012.07.001, 2012

Chapman, A. D.: Principles of Data Quality, version 1.0. Report for the Global Biodiversity Information Facility, Copenhagen, 61 pp, https://doi.org/10.15468/doc.jrgg-a190, 2005

Dewitte, O., Jones, A., Spaargaren, O., Breuning-Madsen, H., Brossard, M., Dampha, A., Deckers, J., Gallali, T., Hallett, S., Jones, R., Kilasara, M., Le Roux, P., Michéli, E., Montanarella, L., Thiombiano, L., Van Ranst, E., Yemefack, M., and Zougmore, R.: Harmonisation of the soil map of africa at the continental scale. Geoderma, 211–212, 138–153. https://doi.org/10.1016/j.geoderma.2013.07.007, 2013

Diaz-Guadarrama, S. and Guevara, M.: Revised database of the Soil Information System of Latin America and the Caribbean, SISLAC version 1.2 [data set], ,https://doi.org/10.5281/zenodo.7876731, 2023

Duan, L., Li, Z., Xie, H., Li, Z., Zhang, L., and Zhou, Q.: Large-scale spatial variability of eight soil chemical properties within paddy fields. Catena, 188, 104350. https://doi.org/10.1016/j.catena.2019.104350, 2020

English, L. P.: Improving Data Warehouse and Business Information Quality: Methods for Reducing Costs and Increasing Profits. New York: John Wiley & Sons, Inc. 518pp, 1999

FAO.: FAO y los Objetivos de Desarrollo Sostenible, https://www.fao.org/sustainable-development-goals/es/, last access: 6 September 2022, 2017

FAO, and IIASA.:. Harmonized world soil database. Food and Agriculture Organization, 43. https://doi.org/312, 2009

FAO, and ITPS: Global Soil Organic Carbon Map (GSOCmap) Technical Report. http://esdac.jrc.ec.europa.eu/content/global-soil-organic-carbon-estimates, 2018

Garg, P. K., Garg, R. D., Shukla, G., and Srivastava, H. S.: Digital Mapping of Soil Landscape Parameters. Springer International Publishing, 2020

GlobalSoilMap Project.: Specifications for GlobalSoilMap products, 52 pp, https://www.isric.org/sites/default/files/GlobalSoilMap_specifications_december_2015_2.pdf, 2015

Gomes, L. C., Faria, R. M., de Souza, E., Veloso, G. V., Schaefer, C. E. G. R., and Filho, E. I. F.: Modelling and mapping soil organic carbon stocks in Brazil. Geoderma, 340, 337–350. https://doi.org/10.1016/j.geoderma.2019.01.007, 2019

Greiner, L., Keller, A., Grêt-Regamey, A., and Papritz, A.: Soil function assessment: review of methods for quantifying the contributions of soils to ecosystem services. Land Use Policy, 69, 224–237. https://doi.org/10.1016/j.landusepol.2017.06.025, 2017

Gutierrez, J., Ordoñez, N., Bolivar, A., Bunning, S., Guevara, M., Medina, E., Olivera, C., Olmedo, G. F., Rodriguez, L., Sevilla, V., and Vargas, R.: Estimación del carbono orgánico en los suelos de ecosistema de páramo en Colombia. Ecosistemas, 29(1), 1–10, https://doi.org/10.7818/ECOS.1855, 2020

Hendriks, C. M. J., Stoorvogel, J., Lutz, F., and Claessens, L.: When can legacy soil data be used, and when should new data be collected instead?. Geoderma, 348, 181–188. https://doi.org/10.1016/j.geoderma.2019.04.026, 2019

Hengl, T., & Macmillan, R. A.: Predictive Soil Mapping with R, OpenGeoHub foundation, Wageningen, the Netherlands, 370 pp, www.soilmapper.org, ISBN: 978-0-359-30635-0, 2019

Hopmans, J. W., Qureshi, A. S., Kisekka, I., Munns, R., Grattan, S. R., Rengasamy, P., Ben-Gal, A., Assouline, S., Javaux, M., Minhas, P. S., Raats, P. A. C., Skaggs, T. H., Wang, G., De Jong van Lier, Q., Jiao, H., Lavado, R. S., Lazarovitch, N., Li, B., and Taleisnik, E.: Critical knowledge gaps and research priorities in global soil salinity. Adv Agron, 169, 1–191. https://doi.org/10.1016/BS.AGRON.2021.03.001, 2021

Instituto Geográfico Agustín Codazzi.: Suelos y tierras de Colombia (Subdirección de Agrología (ed.)). Imprenta Nacional de Colombia S.A, 2016

~~Keskin, H.,~~IUSS Working Group WRB. World Reference Base for Soil Resources 2006, first update 2007. World Soil Resources Reports No. 103. FAO, Rome, 2007~~Keskin, H.,~~ Grunwald, S., & Harris, W. G.: Digital mapping of soil carbon fractions with machine learning. Geoderma, 339, 40–58. https://doi.org/10.1016/j.geoderma.2018.12.037, 2019

Krol, B.: Towards a Data Quality Management Framework for Digital Soil Mapping with Limited Data. In A. E. Hartemink, A. B. Mcbratney, & M. de L. Mendonça-Santos (Eds.), Digital Soil Mapping with Limited Data (pp. 137–149). Springer International Publishing. https://doi.org/10.1007/978-1-4020-8592-5_11, 2008

Lê, S., Josse, J., & Husson, F. FactoMineR: An R Package for Multivariate Analysis. Journal of Statistical Software, 25(1), 1–18. https://doi.org/10.18637/jss.v025.i01, 2008

Leenaars, J. G. B.: Africa Soil Profiles Database, Version 1.1. A compilation of georeferenced and standardised legacy soil profile data for Sub-Saharan Africa. In ISRIC Report 2013/03 (Vol. 03). https://doi.org/10.1201/b16500-13, 2013

Malone, B., Mcbratney, A., Minasny, B., and Laslett, G. M.: Mapping continuous depth functions of soil carbon storage and available water capacity. Geoderma, 154(1–2), 138–152. https://doi.org/10.1016/j.geoderma.2009.10.007, 2009

Malone, B., Minasny, B., and Mcbratney, A.: Progress in Soil Science, Using R for Digital Soil Mapping (A. E. Hartemink, & A. B. Mcbratney (eds.); Springer). http://www.springer.com/series/8746, 2017

Mcbratney, A., Mendonça Santos, M. L., and Minasny, B.: On digital soil mapping. Geoderma (Vol. 117, Issues 1–2). https://doi.org/10.1016/S0016-7061(03)00223-4, 2003

Otte, P., Maring, L., De Cleen, M., and Boekhold, S.: Transition in soil policy and associated knowledge development. Curr Opin Env Sust, 4(5), 565–572. https://doi.org/10.1016/j.cosust.2012.09.006, 2012

Owusu, S., Yigini, Y., Olmedo, G. F., and Omuto, C.: Spatial prediction of soil organic carbon stocks in Ghana using legacy data. Geoderma, 360. https://doi.org/10.1016/j.geoderma.2019.114008, 2020

Paterson, G., Turner, D., Wiese, L., Van Zijl, G., Clarke, C., and Van Tol, J.: Spatial soil information in South Africa:

Situational analysis, limitations and challenges. S Afr J Sci, 111, 28–35. https://doi.org/10.17159/sajs.2015/20140178, 2015

Pfeiffer, M., Padarian, J., Osorio, R., Bustamante, N., Olmedo, G. F., Guevara, M., Aburto, F., Albornoz, F., Antilén, M., and Araya, E.: CHLSOC : the Chilean Soil Organic Carbon database , a multi-institutional collaborative effort. Earth Syst Sci Data, 457–468. https://doi.org/10.5194/essd-12-457-2020, 2020

Pham, K., Kim, D., Yoon, Y., and Choi, H.: Analysis of neural network based pedotransfer function for predicting soil water characteristic curve. Geoderma, 351, 92–102. https://doi.org/10.1016/j.geoderma.2019.05.013, 2019

Poggio, L., De Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., & Rossiter, D. SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. SOIL, 7(1), 217–240. https://doi.org/10.5194/SOIL-7-217-2021, 2021

R Core Team.: R: A language and environment for statistical computing. R Foundation for Statistical Computing, . Available online at https://www.R-project.org/. (https://www.R-project.org/.), 2018

Rossiter, D.: Digital soil resource inventories: status and prospects. Soil Use Manage, 20, 296–301. https://doi.org/10.1111/j.1475-2743.2004.tb00372.x, 2004

Rossiter, D.: Past, present & future of information technology in pedometrics. Geoderma, 324, 131–137. https://doi.org/10.1016/j.geoderma.2018.03.009, 2018

Schulz G.A., Rodríguez D.M., Angelini M., Moretti L.M., Olmedo G.F., Tenti Vuegen L.M., Colazo, J.C., and Guevara M.: Digital soil texture maps of Argentina and their relationship with soil-forming factors and processes. In Geopedology second edition (in production). Springer, Cham., 2022

Silatsa, F. B. T., Yemefack, M., Tabi, F. O., Heuvelink, G. B. M., and Leenaars, J. G. B.: Assessing countrywide soil organic carbon stock using hybrid machine learning modelling and legacy soil data in Cameroon. Geoderma, 367, 13. https://doi.org/10.1016/j.geoderma.2020.114260, 2020

SISLAC.: Sistema de Información de Suelos de Latinoamérica - SISLAC. http://www.sislac.org/#, last access: 2 October 2017, 2013

Varón-Ramírez, V. M., Araujo-Carrillo, G. A., and Guevara, M.: Colombian soil texture: Building a spatial ensemble model, Earth Syst. Sci. Data, 4719–4741. https://doi.org/10.5194/essd-14-4719-2022, 28 October 2022.

Xin, Z., Qin, Y., and Yu, X.: Spatial variability in soil organic carbon and its influencing factors in a hilly watershed of the Loess Plateau, China. Catena, 137, 660–669. https://doi.org/10.1016/j.catena.2015.01.028, 2016

Yao, X., Yu, K., Deng, Y., Zeng, Q., Lai, Z., and Liu, J.: Spatial distribution of soil organic carbon stock in Masson pine (Pinus massoniana) forests in subtropical China. Catena, 178, 189–198. https://doi.org/10.1016/j.catena.2019.03.004, 2019

Zhang, Y., Zhen, Q., Li, P., Cui, Y., Xin, J., Yuan, Y., Wu, Z., and Zhang, X.: Storage of Soil Organic Carbon and Its Spatial Variability in an Agro-Pastoral Ecotone of Northern China. Sustainability, 12(6), 2259. https://doi.org/10.3390/su12062259, 2020

Zhang, Z., Zhou, Y., & Huang, X.: Applicability of GIS-based spatial interpolation and simulation for estimating the soil

organic carbon storage in karst regions. Global Ecology and Conservation, 21, e00849. https://doi.org/10.1016/j.gecco.2019.e00849, 2020