Smart Agricultural Technology 10 (2025) 100735

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

SmartSolos expert: An expert system for Brazilian soil classification

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ARTICLE INFO

Keywords:
Brazilian soil classification system
Data curation
Expert system
Soil classification
Soil data
Soil management

ABSTRACT

We have developed an expert system for Brazilian soil classification according to the official taxonomic system in Brazil. It assists in improving soil data quality, which is important for sustainable agriculture. A rule-based expert system is an appropriate approach for addressing this problem, and SmartSolos Expert is the first one based on the Brazilian soil classification system considering all the classes from the 1st to the 4th level, involving more than a thousand classes. We developed the expert system, made it available through a web Application Programming Interface, and specified a schema for input and output data. Since it always returns accurate classification, it has been used to identify inconsistencies, curate Brazilian soil data, and examine possibilities for improvements to the Brazilian Soil Classification System.

1. Introduction

Soil knowledge is essential for decision-making on issues such as sustainability, food production, and the development of environmental services and public policies. At the international level, the Global Soil Partnership (GSP) was established as a mechanism to develop an interactive partnership to improve soil governance and promote sustainable management [1]. Despite the progress achieved in the study of Brazilian soils, more information is needed for soil management at the national level. One proposal to address this gap is the National Soil Program of Brazil (Pronasolos). The main objectives of this 30-year nationwide program are to resume soil surveys and establish an integrated Brazilian soil database, which needs to include previously collected data as well as data from future works [2].

Advancements in soil knowledge are aligned with the Sustainable Development Goals (SDG), which were adopted by all United Nations Member States in 2015 to promote peace and prosperity for people and the planet [3]. Keesstra et al. [4] show the links between soil science and several SDGs and make recommendations to the soil science community to meet the goals. The efforts outlined in this study are mainly related to goals 12 and 17. Goal 12 relates to ensuring sustainable consumption and production patterns. Its second target is to achieve sustainable management and efficient use of natural resources by 2030. Goal 17, meanwhile, relates to the global partnership for sustainable development. Its targets include enhancing knowledge sharing, policy coherence for sustainable development, and cooperation on science, technology, and innovation access. Additional systematic issues, such as policy and institutional coherence, multi-stakeholder partnerships, and data are also considered.

Soil classification has theoretical and scientific purposes on the origin of soils and their relationships, as well as purposes of practical importance on technological applications, especially in agriculture [5]. In Brazil, the Brazilian Soil Classification System (in Portuguese, Sistema Brasileiro de Classificação de Solos - SiBCS) is the official taxonomic system for soil classification. The first complete documentation of the SiBCS was presented in 1997, and its first edition was published in 1999. With the collaboration of professionals from several research and teaching institutions in the country, it is supported by the Brazilian Agricultural Research Corporation (Embrapa) and the Brazilian Soil Science Society. The constant improvement of SiBCS is a national project since it has nationwide coverage and is being taught in all Brazilian universities [6,7].

In this study, we developed SmartSolos Expert, an expert system for classifying Brazilian soils according to SiBCS, which can be used to validate previously classified soil profiles or to classify new soil profiles. Expert systems seek to provide practical knowledge in a timely and easy-to-access manner, as they can automate the utilization of expert knowledge in real time, explain the reasoning process, and are easily expandible [8]. In addition to the speed and ease in decision-making, Inusah et al. [9] highlight the accuracy of decisions and consistency through the generation of same results given the same inputs.

Therefore, developing an expert system for soil classification

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https://doi.org/10.1016/j.atech.2024.100735
Received 15 August 2024; Received in revised form 17 December 2024; Accepted 17 December 2024
Available online 22 December 2024

contributes to increasing knowledge about Brazilian soils, which is important for sustainable agriculture, public policies, national programs such as Pronasolos, and international initiatives like GSP and the SDGs.

The article is organized as follows. Section 1 presents SiBCS in more detail, showing the challenges of developing an expert system based on SiBCS, and discusses the use of expert systems in agriculture and soil classification. Section 2 presents the material and methods used, along with details of the expert system development. Section 3 provides the results reached by using the expert system with real soil data. Finally, Sections 4 and 5 provide an in-depth discussion of the system, its main contribution, future work, and some final remarks.

1.1. SiBCS

SiBCS is a comprehensive soil classification system that covers the full gamut of known soils in Brazil. Soils consist of roughly parallel sections arranged in layers. The soil profile is the sequence of these layers, called horizons, which reflect the soil formation processes. Fig. 1 shows some photos of soil profiles with well-delimited horizons.

SiBCS relies on numerous attributes, as outlined in Appendix A, and is structured as a taxonomic key up to the 4th categorical level. The classification key is organized hierarchically, with each class taking precedence over the following one. The classification process starts with the key at the 1st level and a search for the class whose definition and requirements are most compatible with the characteristics of the soil being classified. Once the class of the 1st categorical level is confirmed, the process considers the 2nd level, and so on, up to the 4th level. There are recommendations for qualifiers to be applied in the soil classification at the 5th level, and the discussions around the properties to include in the 6th categorical level remain in the preliminary stages [7]. Therefore, the focus of this work is up to the 4th level of SiBCS.

The problem of classifying Brazilian soils is very well structured and documented. However, it encompasses a total of 1187 classes. These are divided into 13 classes at level one (orders), 44 at level two (suborders), 192 at level three (large groups), and 938 at level four (subgroups), as illustrated in Fig. 2. The top line of the figure shows the 13 orders: Argissolo, Cambissolo, Chernossolo, …, Vertissolo. Orders are divided into suborders, which are represented by 44 boxes. For example, Argissolos have five suborders, denoted as PBAC, PAC, PA, PV, and PVA. Each suborder is further divided into large groups, represented by the circles surrounding each box. Each circle contains a number corresponding to the number of subgroups in the large group. For example, there are three large groups within the suborder PBAC, one of which has four subgroups, while the other two have two subgroups each. The Argissolos order contains five suborders, 23 large groups, and 165 subgroups.

In addition to the large number of soil classes, the classification structure involves many complex rules. Table 1 describes an example of soil classes from the 1st level to the 4th, as described by Santos et al. [7]. This table presents just four classes out of all 1187.

To test if a soil profile is a LATOSSOLO, for example, many rules must be considered. Concepts like "latosolic B horizon," "A horizon," or "humic horizon" are complex and involve many conditions. Implementing rules like "Fe_2O_3 content $\geq$ 360 g kg^{-1} soil in most of the first 100 cm of the B horizon (including BA)" in software involves single attributes like Fe_2O_3, simple operations but complex processing, as "most of the first 100 cm of the B horizon (including BA)".

Although SiBCS has been used for many years, no widely used computer program for classifying Brazilian soils is still available. Wagner [10] shows that the interest in expert systems has dropped substantially following a spike in the late 80 s and early 90 s, before the first edition of SiBCS. However, an expert system is an appropriate approach for performing soil classification since it is well-structured and based on rules, and there is a widely used book that systemizes soil classification knowledge.

1.2. Expert systems in agriculture

Expert systems have been used for decades in agriculture [11]; their relevance among the technologies applied to the agricultural sector is highlighted by Elbasi et al. [12]. Some examples of them are ALEES, for agricultural loan evaluation [13]; CULLSOW, for early identification of sows with low prolificacy in commercial pig farms [14]; and Swine-Vet, for diagnosing swine diseases [15]. There are also systems for identifying pests, diseases, and weeds in olive crops [16] and potassium deficiency in cocoa plants [17].

Other expert systems have been developed to apply proper livestock management practices and increase milk and meat production [18], to evaluate land suitability and predict cassava yield [19], and to assess the biodiversity in the life cycle of crops [20] and the impact of soil treatment and mineral nitrogen supply on the energy performance and efficiency of sweet sorghum [21]. Sha et al. [22] evaluated an expert system to optimize fertilization management and concluded that it improved potato productivity and quality.

Several review papers on expert systems in agriculture highlight a variety of such systems [23,24], including specific solutions for irrigation [25,26], oil palm [27], disease diagnoses [28,29], and crop protection [30].

In soil science, especially soil classification, the first mentions of the applicability of expert systems are from the 1980s [31,32]. Fisher and Balachandran [33] developed Stax, a rule-based system for classifying soil according to the United States Department of Agriculture (USDA) Soil Taxonomy. Questions like "Is a natric horizon present?" required the user to know how to interpret the data. Before this system, at least two others had emerged with the same objective. While the first one provided classifications using a database of soil properties, the system developed by McCracken and Cate [31] presented a series of yes/no questions until the class could be determined. Although small and

Fig. 1. Images of soil profiles: examples of Argissolo Vermelho-Amarelo, Argissolo Amarelo, Espodossolo, and Plintossolo.

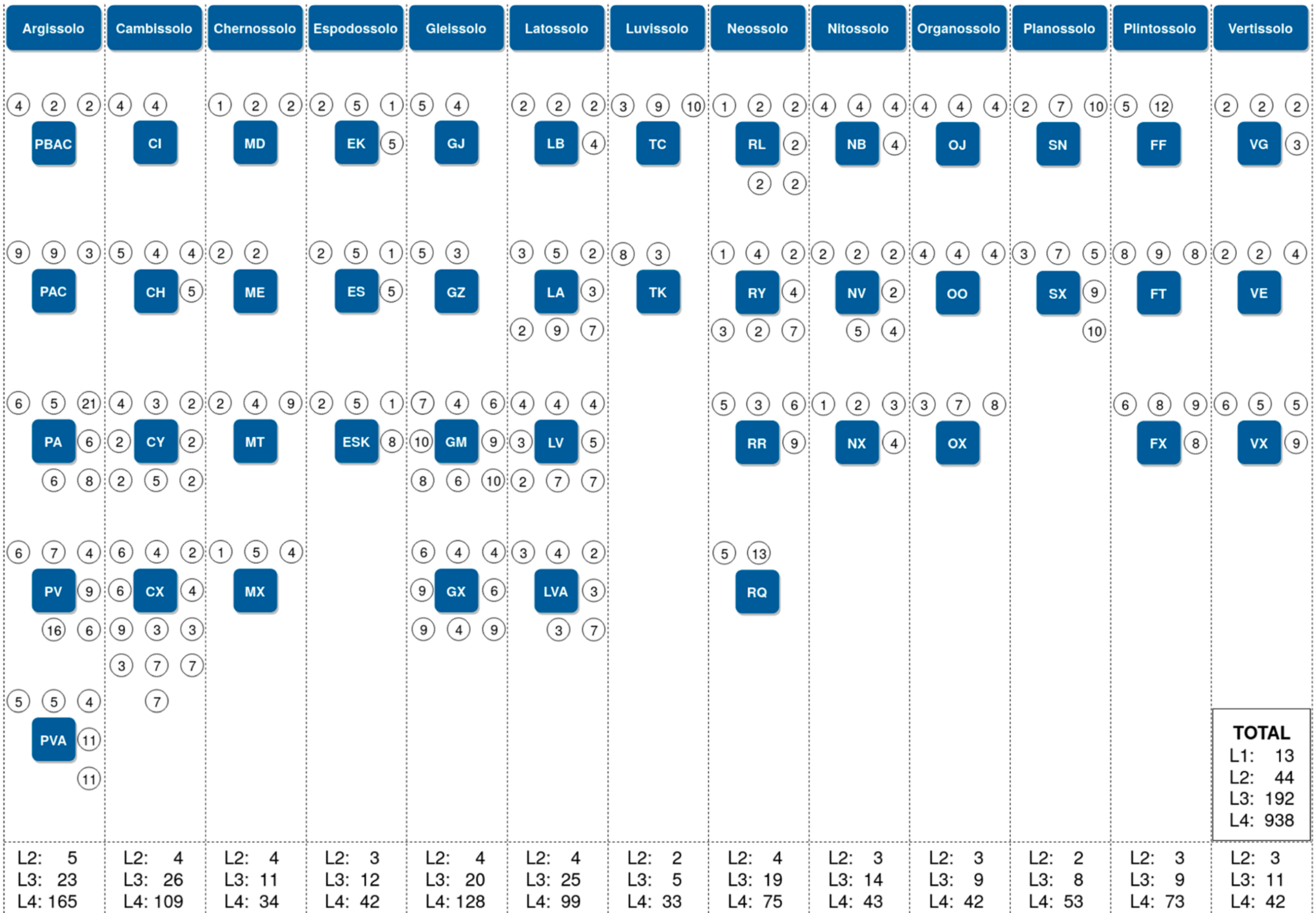

Fig. 2. SiBCS classes.

Table 1
An example of soil classification in the four levels.

Level	Class and description
1: order	LATOSSOLOS are "soils composed of mineral material and a latosolic B horizon preceded by any type of A horizon, within 200 cm from the soil surface or within 300 cm if the A horizon is >150 cm thick."
2: suborder	LATOSSOLOS VERMELHOS are "soils with a hue of 2.5YR or redder in most of the first 100 cm of the B horizon (including BA)."
3: great group	LATOSSOLOS VERMELHOS Perféricos are "soils with a Fe_2O_3 (by H_2SO_4) content $\geq$ 360 g kg^{-1} soil in most of the first 100 cm of the B horizon (including BA)."
4: subgroup	LATOSSOLOS VERMELHOS Perféricos espesso-húmicos are "soils with a humic A horizon and carbon contents of $\geq$ 10 g kg^{-1} to a depth of $\geq$ 80 cm."

simple, it helped detect problems and gaps in the soil taxonomic system and learn the taxonomy. The authors reported that authorities in the field warned that developing an operational expert system would require several months to years of joint efforts by domain experts and knowledge engineers. Some of these systems were based on questions that users must answer, but our objective is to get the classification from the soil data without the need for interaction.

In other applications involving soils, Alsamia et al. [34] proposed a fuzzy expert system with good results in predicting the pollution status of underground water in sandy soils. Sujatha et al. [35] also proposed a fuzzy knowledge-based expert system to determine soil type, although for rating soil suitability in airfield applications. Hadj-Miloud and Djili [36] applied fuzzy logic to a specific soil class of the World Reference Base (WRB) taxonomic system to identify a variation in the degree of belonging membership to a taxonomic concept. For the authors, fuzzy logic could be an effective tool for improving conventional soil classifications. However, in our case, SiBCS is deterministic, and we developed an expert system for the whole taxonomic system, totaling more than one thousand classes.

Galbraith and colleagues [37,38] implemented a prototype based on decision trees to classify soil into four orders with 70 properties to prove the feasibility of developing an expert system for soil taxonomy. Furbee [39] reported a folk expert system for soil classification involving indigenous knowledge in Peru to reflect the thinking of members of a non-Western community about the classification of soils and the management of crops and fields.

None of these previous efforts have dealt with the classification of Brazilian soils. Additionally, a system for automatic and accurate soil classification remains a challenge. Although rule-based expert systems for soil classification have not been in evidence in recent years, we have developed the first accurate expert system to classify Brazilian soil profiles according to the SiBCS automatically.

This article aims to present SmartSolos Expert, an expert system for classifying Brazilian soil profiles according to SiBCS. We show its relevance and impact on soil management.

2. Materials and methods

SmartSolos Expert was developed with the SWI-Prolog language, primarily by a computer scientist and a soil scientist, both with more than twenty years of experience in each area, working in the same organization. Other soil scientists helped by validating data within the system and improving the understanding of the rules of SiBCS.

We did not explore machine learning methods since the SiBCS rules are well-known and described. In this case, implementing the strict rules is better than trying to learn them, especially in a scenario where the classification is so complex, there is no sufficient consistent labeled data to train models, and there is no data sample for many classes.

SmartSolos Expert is accessible via a web Application Programming Interface (API), which enables the sharing of this service and facilitates the integration of information systems, promoting value creation in digital agriculture. The API is available in AgroAPI (www.embrapa.br/agroapi), a platform that provides access to data and models for the agricultural sector [40]. This platform is implemented with an API management solution, whose central role is to manage relationships between API providers and API users [41]. The communication with the API for soil classification is made in JSON (JavaScript Object Notation), a lightweight, text-based, language-independent data interchange format [42].

Some initiatives to compile soil datasets already exist in Brazil, such as BDiA [43], the Brazilian Soil Information System (SISolos) [44], and Soil Data, formerly FEBR [45], currently hosted by the MapBiomas Network. However, they consider different schemas and formats for data representation. To deal with this aspect of the problem, we also proposed a JSON schema based on these initiatives for input into the expert system. It involves >50 attributes, as illustrated by Appendix A.

SmartSolos Expert receives soil data as an input and returns the classification of the corresponding soil profile. Answers are expressed as a classification from the 1st to the 4th level. Fig. 3 shows how the system works. It accepts soil data in JSON format, processes it, and returns the classes in the four levels considered using the attributes ORDEM, SUBORDEM, GRDE_GRUPO, and SUBGRUPO. The input data in the example is very simple, but the system allows many more attributes to be entered, as Appendix A shows. It can also bring a previously defined classification. Thus, a pedologist, a scientist who studies soils, can compare the classification given by the expert system with the previously recorded classification, which allows them to curate the data and use it to make decisions.

One way of calling the system is through a query in the Prolog environment, as in Listing 1, where the identifier of the soil profile is in the input parameter and the output is returned using an X variable with its classification. The profile of this example is an "ORGANOSSOLO HÁPLICO Sáprico típico," with all four levels. In this case, the soil data from the profile SD21ZD/P.22 must be previously loaded.

Listing 2 shows the general structure of the code. Firstly, the soil profile data is recovered by its identifier using facts *profile/2*. Each profile contains a list of horizons used to obtain its classification, with a call to *classify_profile/2*. This is used to test whether the soil profile data satisfies the conditions of any class in the order of precedence given in the SiBCS. If the data does not satisfy the conditions of any order, the system returns "unknown" for all levels because it is impossible to determine the subclasses of soil without its 1st level. However, if it succeeds, it returns a list with the four classification levels, such as the list shown as output for the variable X in Listing 1.

For each class, there are clauses with *class* prefix, like *class_organossolo* and *class_espodossolo*, which receive a list of horizons with all their attributes and check if the soil profile satisfies the condition of the respective class. If it does not, this clause fails, and the system tests the conditions of the following class. Nevertheless, if it satisfies the

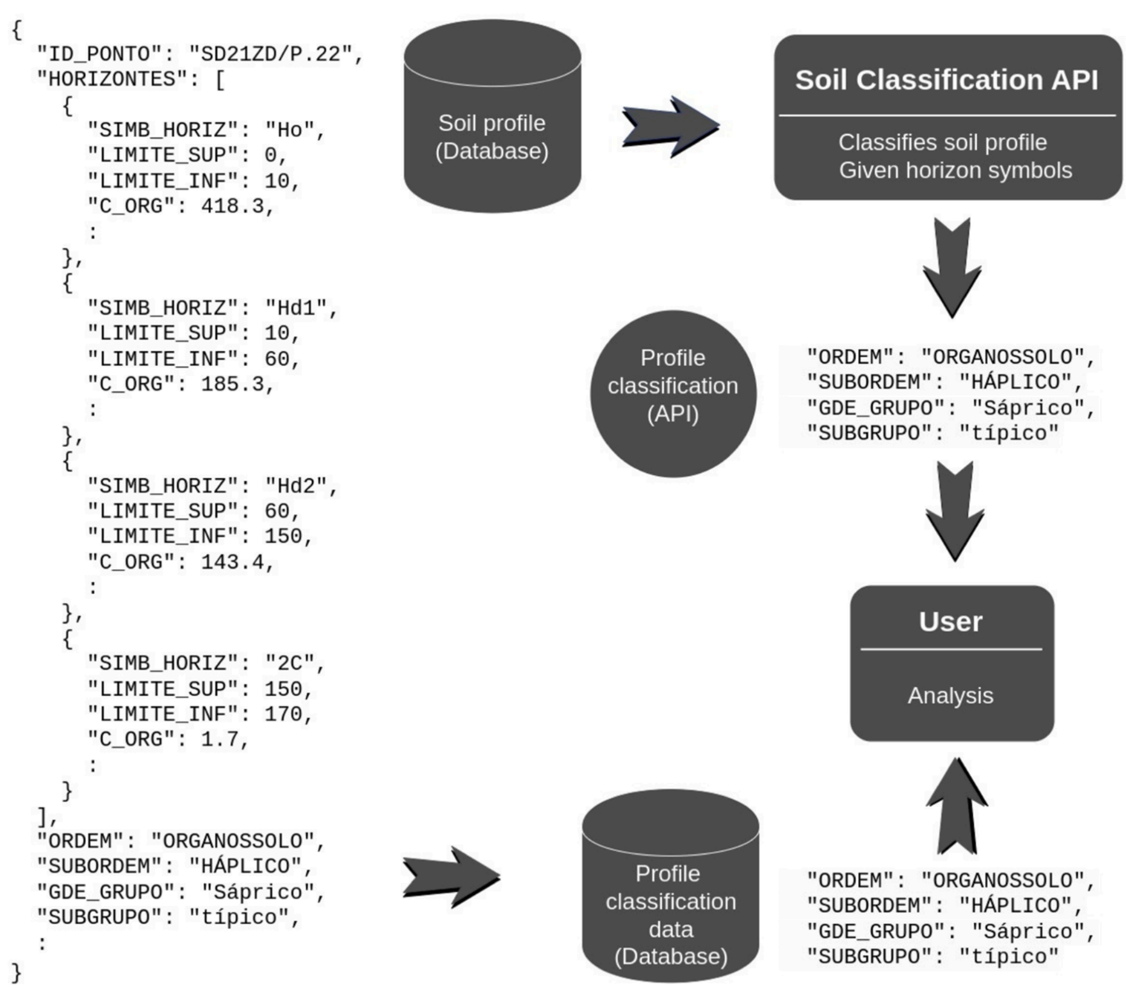

Fig. 3. Example of the expert system usage.

```
?- classify("SD21ZD/P.22", X).

X = ["ORGANOSSOLO", "HÁPLICO", "Sáprico", "típico"]
```

Listing 1. Prolog query.

```
classify(ProfileId, Class):-
  profile(ProfileId, HorizonList),
  classify_profile(HorizonList, Class).

classify_profile(HorizonList, Class):-
  class_organossolo(HorizonList, Class), !.
classify_profile(HorizonList, Class):-
  class_espodossolo(HorizonList, Class), !.
% clauses for all 1st level classes
classify_profile(HorizonList, Class):-
  class_neossolo(HorizonList, Class), !.
classify_profile(_HorizonList,
                ["unknown","unknown","unknown","unknown"]).

class_organossolo(HorizonList,["ORGANOSSOLO"|SubClasses]):-
  organossolo_conditions(HorizonList),
  organo_sub_class(HorizonList,SubClasses).
% similar clauses for class_espodossolo, ..., class_neossolo

organo_sub_class(HorizonList, [Class2, Class3, Class4]):-
  organo_level_2(HorizonList, Class2),
  organo_level_3(HorizonList, Class2, Class3),
  organo_level_4(HorizonList, Class2, Class3, Class4).
% similar clauses for espodo_sub_class, ..., neo_sub_class
```

Listing 2. Prolog structure code.

requirements, the 1st level is set, and the system searches for classification of the following levels. For instance, if the soil profile satisfies the conditions for organossolos, the 1st level is set to "ORGANOSSOLO," and the algorithm searches the sub-classes for the 2nd, 3rd, and 4th levels in this sequence.

The code in Listing 3 is related to the rules shown in Table 1. When a soil profile was already tested as "LATOSSOLO" for the order and "VERMELHO" for the suborder, the predicate *lato_level_3* is used to get the classification for the 3rd level. It can be "Perférrico" if the horizons data meet the conditions of that soil type. In this case, *perferrico/1* returns true, and *lato_level_3/3* returns "Perférrico" for the 3rd level of the soil profile. In the same way, predicate *lato_level_4/4* is used to get the classification for the 4th level. If the soil is a "LATOSSOLO VERMELHO Perférrico", it can be "espesso-húmico" or "húmico", among other possibilities. If it contains a humic A horizon, the rule returns true. The predicate *espesso_humico_or_humico/2* determines if the Class variable receives the value "espesso-húmico" or "húmico." This depends on the depth of horizons and their carbon content.

The system was delivered through a web API to allow more widespread use, with input data in JSON format containing all the necessary information for each soil profile. The classification can be done for just one or several profiles in a request. Listing 4 illustrates the input data

```
lato_level_3(HorizonList, "VERMELHO", "Perférrico"):-
     perferrico(HorizonList), !.

lato_level_4(HorizonList, "VERMELHO", "Perférrico", Class):-
     contains_A_humico_horizon(HorizonList),
     espesso_humico_or_humico(HorizonList, Class), !.
```

Listing 3. Prolog code.

```
{"items":[{
  "ID_PONTO": "DF1",
  "HORIZONTES": [
    {"SIMB_HORIZ": "Hdp", "LIMITE_SUP": 0, "LIMITE_INF": 26,
     "COR_UMIDA_MATIZ": "N",
     "COR_UMIDA_VALOR": 2, "COR_UMIDA_CROMA": 0,
     "COR_SECA_MATIZ": "10YR",
     "COR_SECA_VALOR": 2, "COR_SECA_CROMA": 1,
     "C_ORG": 102, "TEOR_P": 25,
     "PH_AGUA": 5.9, "PH_KCL": 4.7,
     "CA_TROC": 8.6, "MG_TROC": 10.2, "K_TROC": 0.27,
     "NA_TROC": 2.02, "H_TROC": 12.21, "AL_TROC": 0},
    {"SIMB_HORIZ": "Hd1", "LIMITE_SUP": 26, "LIMITE_INF": 48,
     "COR_UMIDA_MATIZ": "N",
     "COR_UMIDA_VALOR": 2, "COR_UMIDA_CROMA": 0,
     "COR_SECA_MATIZ": "N",
     "COR_SECA_VALOR": 3, "COR_SECA_CROMA": 0,
     "C_ORG": 132, "TEOR_P": 18,
     "PH_AGUA": 5.4, "PH_KCL": 3.7,
     "CA_TROC": 1.4, "MG_TROC": 3.9, "K_TROC": 0.11,
     "NA_TROC": 0.56, "H_TROC": 28.79, "AL_TROC": 0.3},
    {"SIMB_HORIZ": "Hd2", "LIMITE_SUP": 48, "LIMITE_INF": 80,
     "COR_UMIDA_MATIZ": "N",
     "COR_UMIDA_VALOR": 3, "COR_UMIDA_CROMA": 0,
     "COR_SECA_MATIZ": "10YR",
     "COR_SECA_VALOR": 3, "COR_SECA_CROMA": 1,
     "C_ORG": 197, "TEOR_P": 6,
     "PH_AGUA": 5.6, "PH_KCL": 3.7,
     "CA_TROC": 8.5, "MG_TROC": 10, "K_TROC": 0.10,
     "NA_TROC": 0.35, "H_TROC": 38.18, "AL_TROC": 0.1}],
  "ORDEM": "ORGANOSSOLO",
  "SUBORDEM": "MÉSICO",
  "GDE_GRUPO": "Sáprico",
  "SUBGRUPO": "típico"}
]}
```


Listing 4. Input data for the expert system. Data from Valladares [46].

with few attributes for just one profile that contains three horizons. The required profile attributes are ID_PONTO, which identifies it, and HORIZONTES, which provides the list of horizons. There are dozens of horizon attributes, but most are optional because sometimes the data is not collected for all soil samples. The names of the four optional attributes that give the annotated classification are the same as the system's output. An example of a response is shown in Listing 5. A pedologist can compare the system's classifications to the previously recorded ones. In this case, the class "MÉSICO" no longer exists in the current SiBCS version as an Organossolo suborder. It is classified as "HÁPLICO." So, a database with this profile can be updated with the current classification.

3. Results

The SmartSolos Expert API is the key result of this work. Freely accessible through AgroAPI, it was used to analyze several soil profiles. Firstly, we used a wider database (BDiA) [43] for evaluating the 1st level of SiBCS. Then, to make a deeper analysis, we assessed the classification in the four levels of 94 soil profiles.

We did a broader analysis of BDiA data with 4467 real soil profile records (Table 2). This database is one of the best in Brazil and is public, easy to obtain on the Internet, and contains classifications from the first four levels of SiBCS for soil profiles. However, because of the large number of records, an analysis was made considering just the 1st level.

```
{"items": [{
   "ID_PONTO": "DF1",
   "ORDEM": "ORGANOSSOLO",
   "SUBORDEM": "HÁPLICO",
   "GDE_GRUPO": "Sáprico",
   "SUBGRUPO": "típico"}
]}
```


Listing 5. Output data for the expert system.

Table 2
BDiA data with real soil profiles.

Order	# Profiles	Consistent	% Consistent
Argissolos	1428	785	54.97 %
Cambissolos	365	243	66.58 %
Chernossolos	86	23	26.74 %
Espodossolos	65	45	69.23 %
Gleissolos	204	167	81.86 %
Latossolos	1157	703	60.76 %
Luvissolos	76	51	67.11 %
Neossolos	465	437	93.98 %
Nitossolos	128	28	21.88 %
Organossolos	13	8	61.54 %
Planossolos	200	124	62.00 %
Plintossolos	247	230	93.12 %
Vertissolos	33	0	0 %
Total	4467	2844	63.67 %

We found that the 1st-level SiBCS classification was consistent with the data in <65 % of the soil profiles, even when relaxing some constraints.

The most common errors found in soil data were caused by differences in SiBCS versions, insufficient data recording, problems with symbol annotations, missing horizon data, typing errors, and different ways of recording the same information. Therefore, it is imperative to more effectively curate soil data in Brazil to improve its soil management.

To make a deeper analysis of soil data, we selected 94 soil profiles from a specific region in Brazil and curated them with the help of SmartSolos Expert, analyzing each profile and updating attributes or classification when necessary. Table 3 shows the number of profiles analyzed for each 1st categorical level (order) of SiBCS. The 'Classification' columns provide the number of soil profiles from each order that were classified by the expert system according to the records previously made by soil scientists. The 'Ln' columns give the number of profiles whose records were correctly classified to the nth level. For example, the classification of nine out of 25 argissolos was consistent with verified records to the 4th level, while 15 argissolos had correct classifications to the 3rd level but not the 4th. Finally, one profile that was actually an argissolo was labeled with entirely different classes. The 'Data Treat.' column indicates how many profiles required data treatment to obtain a consistent record.

Table 3
The classifications and the consistency of data for the analyzed soil profiles.

Order	# Profiles	Classification					Data Treat.
		L0	L1	L2	L3	L4	
Argissolos	25	1	0	0	15	9	13
Cambissolos	11	0	0	1	2	8	7
Chernossolos	2	0	0	0	0	2	1
Espodossolos	3	0	0	0	0	3	0
Gleissolos	8	0	0	3	0	5	2
Latossolos	11	0	0	2	2	7	3
Luvissolos	6	3	0	0	1	2	4
Neossolos	13	1	0	3	0	9	9
Nitossolos	1	0	0	0	0	1	1
Organossolos	1	0	0	0	0	1	1
Planossolos	7	2	0	0	1	4	6
Plintossolos	3	0	0	0	0	3	2
Vertissolos	2	0	0	1	0	1	1
Unknown	1	1	0	0	0	0	1
Total	94	8	0	10	21	55	51

Data must be correct and complete to obtain a correct classification. Even using a high-quality dataset, we have detected misclassifications given by domain experts and errors or absences in attribute values. Changes or additions in attributes were made in 54.3 % (51/94) of the profiles.

After data treatment, the system classified 58.5 % (55/94) of all profiles consistently with the records at all four levels. Meanwhile, 22.3 % (21/94) of profiles were consistent with the 3rd level, with errors only arising in the 4th. In most of these cases, the registered class at the 4th level is no longer valid. As such, these errors were largely caused by incompatibilities across SiBCS versions, and the records had not yet been updated. In 10.6 % (10/94) of profiles, only the 1st and 2nd levels were correct. The classification was completely different from the original in 8.5 % (8/94) of profiles. Therefore, some change in classification was necessary for 41.5 % (39/94) of the profiles. In most cases, this was because the soil profiles were compatible with previous versions of SiBCS but not the current one. Thus, one benefit of SmartSolos Expert is that it helps to update soil data according to the current version of SiBCS in existing datasets. In many instances, inconsistencies were only recognized because the classification obtained by the system was not equal to the one recorded—furthermore, the results from the expert system provided indications of the necessary changes.

It is important to note that the system classified one profile as "unknown" for the 1st level. The current version of SiBCS considers the predominance (> 50 %) of activity clay in the B horizon to classify luvissolos and argissolos. However, in the profile classified as "unknown", 50 % of the B horizon had low-activity clay and 50 % high-activity clay. Therefore, it is not classified either as a luvissolo or as an argissolo. This demonstrates another benefit of the expert system: its ability to validate SiBCS rules using software.

The dataset containing these 94 soil profiles is available in Vaz et al. [47]. It contains, for each soil profile, the original soil sheet, the updated soil sheet after analysis with the help of SmartSolos Expert, and a JSON file with the soil attributes in the input format for the system, including the classification given by the system and verified by a domain expert.

Therefore, analyzing soil profiles with the help of SmartSolos Expert made it easier to identify errors and inconsistencies and allowed more reliable data curation. Some studies based on these results have been presented at major Brazilian and international conferences on soil science and agroinformatics. This process also helped to identify some issues in SiBCS rules. As a result, suggestions for changes to the SiBCS were sent to those responsible for maintaining it, which are under evaluation for possible incorporation into a new version. Additionally, the development of the expert system made it possible to analyze soil data representation, create a format for the data used for soil classification, and document possible changes in how this type of data is represented.

4. Discussion

Cullen and Bryman [48] pointed out many factors that lead to the success of expert systems. Our system involves several of them: its domain is narrow; it was initiated in the organization and supported by its higher management; it was not initiated by academics; it was developed in response to solving the specific problem of soil classification, which has a clear specification, and it is rule-based and was developed in Prolog.

According to Dale et al. [49], expert systems may have to deal with imprecise information because of measurement difficulties, the descriptors involved are human assessments of an interval nature, or simply because several experts disagree. All these situations happen in soil classification. It is difficult to measure some properties because of natural conditions and the imprecision of instruments; some soil descriptors are subjective and involve human assessments, and pedologists often disagree about the correct classification. These sources of imprecision and other issues compromise the quality of soil data. SmartSolos Expert helps soil scientists to identify inconsistencies between the soil data and its classification. Dale et al. [49] also pointed out that an expert system incorporating a soil taxonomy system could be used to check for ambiguity, redundancy, and contradiction. Therefore, it could be used to evaluate changes to the USDA Soil Taxonomy system or other national systems. SmartSolos Expert does help to detect ambiguities, redundancies, and contradictions of the SiBCS when it is codified in software and tested on real data.

For Eriksson [50], there are also some obstacles to knowledge acquisition related to human factors. It is hard to articulate knowledge and elicit an expert's conceptual domain model. Typically, a representational mismatch exists between how experts express themselves, how knowledge engineers think of the expert's knowledge, and the knowledge representation used in a computer system. The author also points out that the effort devoted to knowledge acquisition is often too short compared to the problem addressed. In addition, Wagner et al. [51] state that manual knowledge acquisition techniques require enormous time and labor from both the knowledge engineer and the domain expert. In a study with seventy applications, Cullen and Bryman [48] estimated the average time spent on knowledge acquisition to be around 16 person-days. This is very little time for the problem we are dealing with. The complexity of soil classification demanded much more time in knowledge acquisition.

SiBCS is published in a book that presents the rules of classification in natural language. Some ambiguities and contradictions cause misunderstandings and different interpretations, even among soil scientists. There is no mathematical formalism available for these rules. Therefore, the expert system code also represents a document without ambiguities that permits a deterministic soil classification. Since the rules and the input data are understood, the knowledge engineer has to represent them properly. The rules were represented in Prolog, which was a challenge given their complexity and the large number of classes. However, this contributed to the system's success because, generally, the success of an expert system depends on identifying suitable domains and appropriate forms of knowledge representation [48].

Wagner [10] performed a content analysis of 311 case studies in a project that covers thirty-three years of expert system case studies from 1984 to 2016. The author confirmed that research in this field had moved away from the classic expert system with human experts to a hybrid model incorporating AI tools and techniques. In our case, however, the classic expert system was appropriate since the conditions for using other AI tools and techniques, like sufficient curated data, are absent. The author reports that most applications continue to focus on using rules for knowledge representation, but Prolog is no longer in regular use. Despite that, we used Prolog to represent the rules of the system, and it contributed to its success. Finally, some lower-impact systems were developed in agriculture and scientific research, areas addressed by this project. The author states that the reason might be a lack of infrastructure or managerial expertise to implement these systems throughout the organization successfully. However, this is not applicable in our case.

According to Wagner et al. [51], the impact of expert systems can be quantified based on the changes brought about by its introduction, represented on an ordinal scale ranging from 1 for prototypes to 7 for systems that result in cost savings and structural changes to the organization. In the middle are validated systems without reported impacts. Although the authors did not deepen how to evaluate expert systems with the scale they proposed, it is clear that SmartSolos Expert would have a grade near 7, the maximum score.

Firstly, it is not just a prototype. It has been tested and validated and is freely available through an API in AgroAPI (www.embrapa.br/agroapi), an initiative by Embrapa to promote agricultural value creation by offering data and services through APIs.

Soil scientists have used it to analyze and curate Brazilian soil data profiles. With the help of the system, many soil profile records have been curated and updated. Soil data with better quality provide benefits for scientists as well as support public policy.

The international and Brazilian Soil Science and Agroinformatics communities already recognize the relevance of this expert system for soil classification. Results obtained with the help of the system were presented at the main congresses of these communities, highlighting its importance for soil data curation.

Although the system cannot be measured by cost savings and structural change to the organization, as advocated by Wagner et al. [51], the impact of the system goes beyond the organization through its impact on national public policy. It is sure to involve economic savings since pedological surveys are costly, and better use of existing data will result in cost savings.

Another benefit is related to the improvement of SiBCS itself. With the help of SmartSolos Expert, ambiguities and inconsistencies were identified in the SiBCS and its publication [7]. Since SiBCS is an open taxonomic system that is constantly being developed, suggestions for changes were sent to its authors and maintainers.

According to Lezoche et al. [52], some impacts of expert systems are related to making good and real-time, low-cost expert-level decisions by non-experts. SmartSolos Expert makes it possible to use the knowledge of many soil classification experts by simply accessing the system in real time via an API.

Pedologists can use the system to compare the result with the previously recorded classification. For future work, the system can be improved to check the validation of a given classification. If correct, the system returns success, but if not, it could show messages explaining why the classification differs from the input. In addition to making it easier to identify errors or inconsistencies, it would be very useful for learning soil classification. Another feature of the system can be the validation of horizon symbols. In the current version, the horizon symbols are assumed to be provided correctly, but mistakes or incompleteness may be present. Some checking can be done by software since the symbols are also determined, at least partially, by other soil attributes. For this, however, additional attributes would be necessary as input.

Not every class was tested with real soil profile data because there are so many soil classes in the SiBCS. As the system validation demands so much time from soil experts, some code errors may occur. However, since it is deterministic and based on the SiBCS rules, every soil profile record must be correctly classified. If this is not the case, the data or the code should be updated. In most cases, data is changed because of errors in data annotation, but when some code error is found, it is fixed, and the system starts giving correct answers. Therefore, SmartSolos Expert always returns the accurate classification for all soil profiles if the input data is correct.

The system strictly follows the SiBCS rules. Sometimes, a difference of 1 cm in the depth of a horizon can result in a totally different classification. However, in some cases, soil experts tend to overlook small differences and come to divergent classifications. In future studies, some flexibility can be considered depending on soil attributes that are more relevant to the tested classes.

This work also showed the importance of the data annotation quality. Digital technologies can only be created and exploit data if it is properly recorded. Tools like SmartSolos Expert can improve data quality, but it is also important to provide good user interfaces to engage the target audience.

5. Conclusions

We have presented SmartSolos Expert, an expert system for Brazilian soil classification according to the SiBCS in four categorical levels. It helps to build knowledge of Brazilian soils, which is important for sustainable agriculture and public policy and is aligned with initiatives like the SDGs, GSP, and Pronasolos.

The main contribution of SmartSolos Expert is related to improving soil data quality. This provides several benefits: (i) it can be used to validate previously classified profiles and to classify new soil profiles; (ii) it can contribute to developing SiBCS; (iii) it is a rule-based system so that it can be incrementally developed and validated; and (iv) it increases the availability of knowledge on Brazilian soil classification since it is documented not only in the form of publication but also in software code.

The problem of soil classification according to SiBCS is very well structured, based on rules, and documented in widely used publications. Furthermore, the conditions for implementing the system were present in this work. Despite its complexity and the decreasing interest in this technology, we showed that developing an expert system is appropriate in this case. There are many expert systems related to agriculture. However, there is no system like the one we developed for soil classification. It is the first expert system involving all the classes until the 4th level of SiBCS.

In this article, we explained some system details, like the structure of rules, input and output data, and the use of a web API for accessing it. Many soil profile records were already updated in soil databases with the help of the system in data curation, and suggestions for changes in SiBCS publication were forwarded to its maintainers.

CRediT authorship contribution statement

Glauber José Vaz: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Luís de França da Silva Neto:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing. **Jayme Garcia Arnal Barbedo:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics Statement

Not applicable: This manuscript does not include human or animal research.

Acknowledgements

This work was supported by the Brazilian Agricultural Research Corporation (Embrapa) [SEG 23.14.01.017.00.00].

Appendix A. Input data

Table A.4 presents the attributes for a soil profile and Table A.5 shows the attributes for a horizon of a soil profile. The values of some attributes are based on Santos et al. [53] and Instituto Brasileiro de Geografia e Estatística [54].

Table A.4
Soil profile attributes in input data.

Attribute	Type	Description
ID_PONTO	string	Soil profile identification
HORIZONTES	horizon array	Horizons of the profile
DRENAGEM	integer	Drainage [1: excessively drained, 2: strongly drained, 3: intensely drained, 4: well drained, 5: moderately drained, 6: imperfectly drained, 7: poorly drained, 8: very poorly drained]
ORDEM	string	Soil classification: 1st categorical level (order)
SUBORDEM	string	Soil classification: 2nd categorical level (suborder)
GDE_GRUPO	string	Soil classification: 3rd categorical level (great group)
SUBGRUPO	string	Soil classification: 4th categorical level (subgroup)

Table A.5
Soil horizon attributes in input data.

Attribute	Type	Description
SIMB_HORIZ [required]	string	Horizon symbol
LIMITE_SUP [required]	integer	Upper limit of the horizon (cm from the soil surface)
LIMITE_INF [required]	integer	Lower limit of the horizon (cm from the soil surface)

(*continued on next page*)

Table A.5 (*continued*)

COR_UMIDA_MATIZ	string	Hue (moist color)
COR_UMIDA_VALOR	integer	Value (moist color)
COR_UMIDA_CROMA	integer	Chroma (moist color)
COR_SECA_MATIZ	string	Hue (dry color)
COR_SECA_VALOR	integer	Value (dry color)
COR_SECA_CROMA	integer	Chroma (dry color)
COR_MOSQ_MATIZ_N*	string	Hue (mottle N). *N = 1, 2, ...
COR_MOSQ_VALOR_N*	integer	Value (mottle N). *N = 1, 2, ...
COR_MOSQ_CROMA_N*	integer	Chroma (mottle N). *N = 1, 2, ...
ESTRUTURA_GRAU	integer	Structure degree [1: no, 2: weak, 3: moderate, 4: strong]
ESTRUTURA_TAMANHO	integer	Structure size [1: very small, 2: small, 3: medium, 4: large, 5: very large, 6: extremely large]
ESTRUTURA_TIPO	integer	Structure type [1: laminar, 2: prismatic, 3: columnar, 4: angular blocks, 5: subangular blocks, 6: granular, 7: lumpy]
CEROSIDADE_GRAU	integer	Clay films degree [1: no, 2: weak, 3: moderate, 4: strong]
CEROSIDADE_QUANTIDADE	integer	Clay films quantity [1: low, 2: common, 3: abundant]
TRANSICAO_GRAU	integer	Transition distinctness [1: abrupt, 2: clear, 3: gradual, 4: diffuse]
TRANSICAO_FORMA	integer	Transition topography [1: smooth, 2: wavy, 3: irregular, 4: broken]
CONSISTENCIA_SECO	integer	Dry-soil consistency (hardness) [1: loose, 2: soft, 3: slightly hard, 4: hard 5: very hard, 6: extremely hard]
CALHAU	integer	Cobbles quantity (g/Kg)
CASCALHO	integer	Gravel quantity (g/Kg)
AREIA_GROS	integer	Coarse sand quantity (g/Kg)
AREIA_FINA	integer	Fine sand quantity (g/Kg)
SILTE	integer	Silt quantity (g/Kg)
ARGILA	integer	Clay quantity (g/Kg)
PH_AGUA	double	Soil pH in water
PH_KCL	double	Soil pH in KCl
C_ORG	double	Organic-carbon content (g/Kg)
CA_TROC	double	Exchangeable calcium (cmol/Kg)
MG_TROC	double	Exchangeable magnesium (cmol/Kg)
K_TROC	double	Exchangeable potassium (cmol/Kg)
NA_TROC	double	Exchangeable sodium (cmol/Kg)
AL_TROC	double	Exchangeable aluminium (cmol/Kg)
H_TROC	double	Exchangeable hydrogen (cmol/Kg)
P_ASSIM	double	Available phosphorus (mg/Kg)
COND_ELETR	double	Electrical conductivity (dS/m)
EQUI_CACO3	double	Calcium Carbonate Equivalent (g/Kg)
TEOR_FE	double	Iron content (g/Kg)
RETRATIL	boolean	Soil with a retractable character?
COESO	boolean	Soil with a cohesive character?
FLUVICO	boolean	Soil with a fluvic character?
SOMBRICO	boolean	Soil with a sombric character?
REDOXICO	boolean	Soil with a redoxic character?
MATERIAIS_PRIMARIOS	boolean	Soil with alterable primary materials?
ATIVIDADES_HUMANAS	boolean	Soil with past human activity?
PLACICO_TOPO	boolean	Soil with a placic horizon?
PLINTITA_MENOR_15	boolean	Plinthite content < 15 %?
MANGANES	boolean	Manganese occurrence?
LAMELA_SUP	integer	Lamellae upper limit (cm from surface)
LAMELA_INF	integer	Lamellae lower limit (cm from surface)
LAMELA_TEXTURA	integer	Lamellae texture [1: sand, 2: loamy sand, 3: sandy loam, 4: loam, 5: sandy clay loam, 6: silt clay loam, 7: clay loam, 8: silt loam, 9: clay, 10: sandy clay, 11: silty clay, 12: silt, 13: clayey, 14: organic, 15: fibric, 16: indiscriminate]

Data availability

We have shared the link to our data

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