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When can legacy soil data be used, and when should new data be collected instead?

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ABSTRACT

Soil data requirements and soil data acquisition tools and techniques have changed over recent decades. In general, soil scientists can: i) collect new data in the field and ignore the data that are available, ii) rely entirely on legacy soil data or iii) combine available legacy data with new data collection. This study aims to analyse and discuss the choices soil scientists make to balance between the use of legacy soil data and the collection of new soil data. A literature review on soil data acquisition was carried out and illustrated that the use of legacy soil data is still often very limited, while soil data availability increased over recent decades. Studies that use legacy soil data often use conventional soil data, which are criticised in literature. A regional and local case study was carried out to illustrate the choices that have to be made for obtaining the required soil data. It turned out that both case studies preferred to combine new soil data collection and legacy soil data. Many of the reviewed studies could reduce their sampling effort by making better use of available data, tools and techniques. Besides, soil scientists can help facilitating soil data acquisition by developing soil data warehouses.

1. Introduction

The soil science community has a long history in collecting and describing soil information in standardized ways through e.g., guidelines for soil profile descriptions (FAO, 2006), standardized soil classification systems (Soil Survey Staff, 2014; IUSS Working Group WRB, 2015), and soil survey manuals (Soil Science Division Staff, 2017). Their successful approach resulted in a plethora of conventional soil surveys around the world at different scales (Omuto et al., 2013). These soil surveys were developed in times that soil data were used for the basic understanding of soil-landscape relationships, land evaluation and land use planning. Over the past decades, various changes have taken place in soil data requirements as well as in the data, tools and techniques for soil data acquisition:

1. The amount of legacy soil data, i.e., all existing soil data, increased. Almost 30% of the globe has been mapped beyond 1:1 million scale using conventional soil surveying techniques (Nachtergaele and Van Ranst, 2003; Omuto et al., 2013). The conventional soil maps were accompanied by representative soil profile descriptions, which became available in harmonized soil databases. The World Soil Information Service (WoSIS) Soil Profile Database is an example of such a database and includes some 100,000 soil profiles (Ribeiro et al., 2018). Other sources of legacy soil data can, for example, come from monitoring experiments, agronomic experiments or visual soil assessments.
2. The introduction of open data sources has increased the accessibility of soil data. Many of the soil data became easily accessible through a range of web portals, such as the European digital archive on soil maps (Panagos et al., 2011) and the World Soil Survey Archive and Catalogue (Hallett et al., 2006). Besides web portals, mandatory data sharing policies are increasingly being adapted and seem to have effect on sharing new soil data.
3. Some soil data already became outdated and various efforts started to rescue (e.g., Cambule et al., 2015; Rossiter, 2008) and update the data (Kempen et al., 2009; Steinbuch et al., 2018).
4. Soil data are nowadays dominantly applied in interdisciplinary studies that contribute to global challenges. The way soils can contribute to these global challenges are described in 17 UN Sustainable Development Goals (SDGs) (Bouma, 2014; Keesstra et al., 2016). Quantitative simulation models are increasingly being used for these interdisciplinary studies. Soil data is often one of the

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many input data these simulation models require.

5. A direct consequence of requiring many different input data is that funding reserved for the collection of new soil data reduces. As a result, more cost-efficient methods for data collection developed, e.g., digital soil mapping (McBratney et al., 2003), or studies have to rely entirely on legacy soil data to reduce costs.
6. Rapid improvements in computing technology and capacity stimulated the development of new soil mapping techniques. These techniques make use of sophisticated statistical or mechanistic models and combine, in general, auxiliary information, e.g., environmental data that represent the soil forming factors, and soil observations. Examples of these new soil mapping techniques are digital soil mapping (McBratney et al., 2003), the disaggregation of conventional soil maps (e.g., Kerry et al., 2012; Stoorvogel et al., 2017) and data mining (Armstrong et al., 2007).

These changes forced studies to obtain the required soil data differently. In general, three options are available to obtain the required soil data: i) if funding allows, collect new data and ignore the legacy soil data that are available, ii) rely entirely on legacy soil data, and iii), combine available legacy data with new data collection. The latter option seems to be a logical choice, because both have their advantages and disadvantages. For example, legacy data can provide insight in soil variation that can help optimizing sampling schemes or new soil data collection can provide data on soil characteristics that cannot be obtained from legacy soil data. Question remains on the choices existing studies make in order to obtain the required soil data and whether these choices aim for the optimisation of soil data acquisition? This paper aims to analyse and discuss the choices soil scientists make to balance between the use of legacy soil data and the collection of new soil data.

We will first review to what extent studies have been relying on legacy data and on new soil data collection and how this changed over time. We hypothesized that studies at the regional scale typically rely on legacy data and studies at the local scale mainly rely on the collection of new soil data (Fig. 1). In the context of the changes described previously, it is also expected that studies increasingly rely on legacy soil data. These hypotheses will first be evaluated in a literature review. Subsequently, we carried out two case studies to illustrate the choices that have to be made in order to obtain the required soil data. The first case study deals with a local study on managing soil organic matter stocks in a Costa Rican banana plantation. The second study deals with a regional study on the effect of Climate-Smart Agricultural (CSA) practices on rain-fed maize yields under future climate scenarios.

2. Literature review on the use of soil data

2.1. Introduction

To obtain the required soil data, legacy soil data can be used or new soil data can be collected. Both options have limitations. Conventional soil maps are criticised as being: i) dominantly qualitative, (ii)

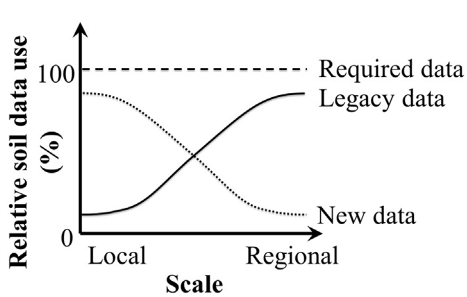

Fig. 1. This study hypothesizes that studies at the regional scale typically rely on legacy data and studies at the local scale mainly rely on the collection of new soil data.

outdated, (iii) not spatially continuous, (iv) inconsistent, and (v) lacking quality assessment (e.g., Sanchez et al., 2009; Heuvelink, 1998; Renschler and Harbor, 2002; Hengl et al., 2014), whereas the collection of new soil data is criticised as being: (i) expensive and time-consuming, (ii) often based on point observations, (iii) logistically difficult (e.g., accessibility), (iv) a trade-off between quality and quantity and (v) limited to the current conditions (McBratney et al., 2003; Hengl et al., 2017). These limitations make us curious to the choices that have to be made in order to obtain the required soil data. In this section, a literature review is carried out to analyse where soil scientists source their soil data and how this changed over time.

2.2. Methodology

The literature review is based on 120 studies published in Geoderma. Studies that use soil data were selected based on publication order. The first 60 studies published in 1967 to 1971 and the first 60 studies published in 2015 to 2016 were selected (Appendix A). Data were extracted on: (i) the spatial scale of the study, (ii) the proportion (%) of new soil data collected, (iii) the proportion of legacy soil data used and (iv) the proportion of auxiliary data used for the analysis. To better understand the factors that drive the decision on which soil data to choose (e.g., costs, efficiency), additional information is obtained on the role newly collected soil data and legacy soil data play in the study. The four authors of this manuscript analysed 40 studies each of which 10 had an overlap with another author. As such, 40 studies were analysed by two persons to test the consistency in the interpretation.

To determine the scale of the study, the research objective, the methodology, and the conclusions were taken into account. Local studies included fields, farms and villages, and regional studies included watersheds, landscapes and countries (FAO, 1993). The proportion of new soil data collected for the analysis and the proportion of legacy soil data used for the analysis add up to 100%, assuming that these two soil data sources meet the soil data requirements. New soil data included data that were obtained by monitoring, experiments, soil sampling, interviews and visual observations. As the availability of auxiliary data (e.g., satellite imagery) increased rapidly over recent decades and can play an important role, we also looked at changes in the use of auxiliary data over time.

2.3. Results and discussion

Studies published in 1967–1971 mostly collected the required soil data at all scale levels (Fig. 2). Only two studies completely relied on legacy data, and 12 studies combined the collection of new soil data and legacy data considerably. In 2015–2016, five studies completely relied on legacy data, and 10 studies combined the collection of new soil data and legacy soil data considerably. On average, studies of 1967–1971 as well as studies of 2015–2016 used legacy soil data for approximately 12% of the total soil input data. However, in contrast to the studies published in 1967–1971, there is now a very clear relation with scale. Studies at local studies hardly use any legacy data and regional studies rely predominantly on legacy data, which means that the first hypothesis can be accepted. Over recent decades, the number of studies that used auxiliary information for the analysis doubled according to our review. We also observed that studies of 1967–1971 collected and used new soil data in combination with qualitative legacy data to better understand the soil system. The more recent studies collected new soil data to obtain data that are not provided by legacy soil data.

In some studies, legacy soil data play a very limited role. The data is, for example, only used to describe the soil types that occur in the study area (Shirani et al., 2015; Bughio et al., 2016; Szymański et al., 2015). No use is made of the (spatial) information that legacy soil data can provide for the interpretation of the results or setting up sampling schemes. About 85% of the 2015–2016 studies still collect new soil data

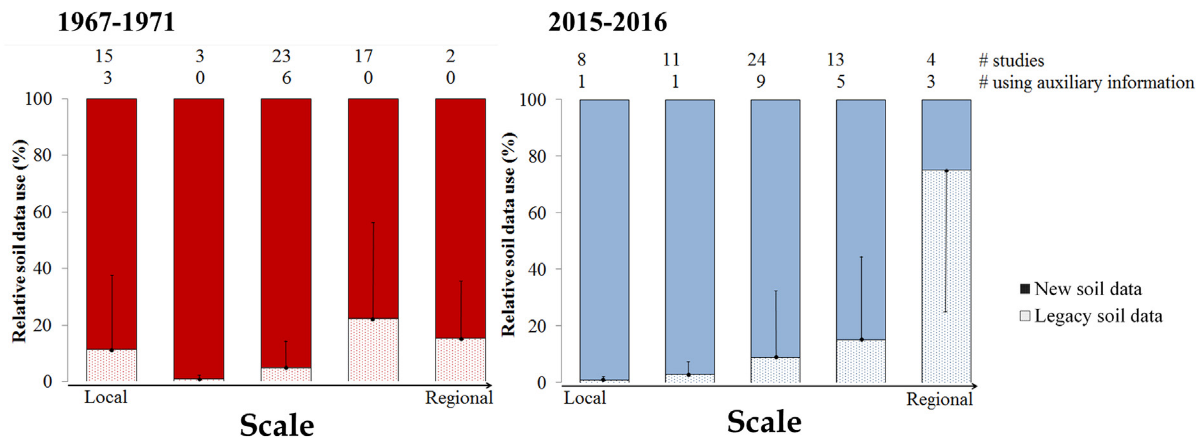

Fig. 2. The relative distribution (in %) and standard deviation (black line) of legacy soil data use and new soil data collection analysed in 60 studies of 1967 to 1971 and 60 studies of 2015 to 2016. The number of studies each bar represents and how many of these studies used auxiliary information are mentioned above the bars.

and hardly use legacy soil data. This is in contrast with the development of new soil data products that aim to better meet the soil data requirements.

New soil data are mainly collected to provide insight in the current conditions or the effects of a particular treatment, e.g., soil tillage (Jin et al., 2017), whereas legacy data may be essential to provide insight in past conditions. Studies using legacy soil data typically make use of a single data source such as the Harmonized World Soil Database (Fischer et al., 2008). Karamesouti et al. (2016) was the only study that checked multiple soil databases. The limited use of legacy soil data needs attention by soil scientists given the valuable information that it contains (Bonfante and Bouma, 2015).

The studies that were conducted by two different reviewers were consistent in the analysis, despite difficulties in estimations of the spatial scale. In three cases the estimation of the authors differed two scale levels.

3. Exploring the use of legacy data in local studies

Local studies typically require detailed soil data that is not available as legacy soil data. Therefore, these studies often rely on the collection of new soil data, which was also confirmed by the literature review. However, legacy soil data can still play an important role to guide soil data collection and interpreting the results of a study. This case study aims to explore and analyse the use of legacy soil data in a local study. The study analyses whether soil fertility can be sustained when crop residues are removed from banana plantations.

3.1. Introduction

Costa Rica is one of the main banana exporters with one of the highest productions worldwide (≈50 t bananas/ha/yr; FAO, 2016). However, the Costa Rican banana sector is under pressure to produce bananas in a more sustainable way, because of intensive use of agrochemicals and large monoculture plantations. In a wide range of initiatives, the sector aims to make the production more environmentally friendly (Stoorvogel et al., 2004). The production of bananas coincides with the production of large quantities of crop residues. The crop residues are left in the field (stems and leaves) or returned to the field in a later stage (mainly bunch stalks from the packing plant). As such, the crop residues recycle large amounts of nutrients to the soils and maintain soil organic matter (SOM) stocks. However, the crop residues are also seen as a valuable asset of raw material. Crop residues can be used in various ways like fibre for paper and biomass for biofuel. A recent development is the use of banana fibres to produce ecologically friendly pallets by the Dutch Limited company Yellow Pallet B.V (www.yellow-pallet.com). The study formed the basis for the location specific repercussions of crop management on soil management and the development of a business plan.

3.2. Research implementation

The humid lowlands in the northeast of Costa Rica are the basis for the national banana production with a total production area of 42,000 ha. The area exhibits considerable soil variation that may have impact on the results. A soil map for the region was published by Wielemaker and Vogel (1993). The area can roughly be subdivided in a western part with volcanic ash soils and an eastern part with non-volcanic soils. This subdivision is commonly being used in e.g., banana research and fertilizer recommendations in the region. In both parts, a banana plantation was selected that was open for research and had representative soil conditions: the Banatica plantation (10°15′28.29″N, 83°44′43.39″W) with andic Eutropepts and dystric Vitrudands in the Western part and the San Pablo plantation (10°6′45″N, 83°22′53″W) with typic Eutropepts and Humitropepts in the Eastern part (soil classifications is based on the Soil Survey Staff, 1992). The long-term effects of management changes on SOM stocks in a perennial crop can be analysed in different ways. One could do long-term experiments, but in the case of Yellow Pallet, the available resources were limited and commercial interests required an answer within a year. As an alternative, various modelling approaches to evaluate SOM dynamics are available (Shibu et al., 2006). Although one could rely on existing studies and data, it became apparent that most of these studies did not focus on the banana crop. In this study we use a simple description of SOM dynamics following Johnson et al. (2014). The approach, illustrated in Fig. 3, assumes that crop residues are the only organic matter input. Two conversion factors are important in the model: the humification and decay rate. The humification rate estimates the fraction of crop residues that enters the SOM pool, and the decay rate estimates the fraction of SOM that converts into CO_2, i.e. mineralization rate. The humification rate depends on the characteristics of the crop residues as well as on the soil and climatic conditions. The mineralization rate

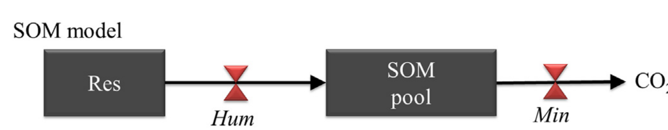

Fig. 3. The soil organic matter (SOM) model assumes that crop residues (*Res*) are the only organic matter input. Two conversion factors are considered: humification rate (*Hum*) and mineralization rate (*Min*). The humification rate estimates the fraction of crop residues that enters the *SOM pool* and the mineralization rate estimates the fraction of SOM that converts into CO_2.

strongly depends on the characteristics of the soil organic matter, soil properties, e.g., clay content, and climatic conditions. Both conversion factors are extremely hard to measure. Therefore, often fixed default values or literature data are being used. Alternatively, the model can be initialized and model parameters can be set through a model spin up. Soil properties are likely to change rapidly after the initial establishment of the banana plantations as shown by Powers (2004). Many banana plantations have been established > 10 years ago and management has been relatively constant over time. As a result, one can expect that the current soil conditions reached a steady state. A steady state would imply: $es \cdot Hum = SOM \cdot Min$, with *Res* being the amount of crop residues entering the system (in kg/ha), *Hum* the Humification rate (in %/year), *SOM* the soil organic matter stock (in kg/ha) and *Min* the mineralization rate (in %/yr). We can derive *Min/Hum* from a system that is known to be in equilibrium and as such we can calculate the long-term effect of changing the organic matter input.

We point out the decisions that were made in order to obtain the required soil data, by evaluating the potential of both: the use of legacy data and the collection of new data.

Legacy data that was used:

- Long-term monitoring data of topsoil SOM contents were available for two plantations, the San Pablo plantation and the Rebusca plantation (Fig. 4). As part of their annual evaluation of soil quality, they measured for 15 consecutive years an average SOM for both banana plantations. The plantations are located on similar soils as the Banatica plantation and therefore these legacy data were useful for obtaining information on the variation in SOM content over time. The data showed an almost stable or slight decrease in SOM content under current management practices.

New data that was collected:

- Composite soil samples were taken in three experimental plots of approximately 50 × 50 m. Samples on the topsoil (0–30 cm) and subsoil (30–60 cm) were taken to estimate the actual SOM stocks of the upper 60 cm of the soil profile. The model requires data on SOM stocks to start the model run.
- At the two plantations, SOM contents on two plots of 2 × 2 m were monitored. In one plot the crop residues were removed, and in the other plot the crop residues were left on the plot. The SOM content was measured at the initial stage of the experiment and after one year. These data confirmed that changes in SOM stock are not visible within a year.
- To estimate the organic matter input, field data on plant density and quantities of crop residues were systematically collected in the three experimental plots in August 2012 on a well-drained sandy loam Eutropept in the San Pablo plantation and loamy fertile and well-drained dystric Vitrudands in the Banatica plantation.

The model was calibrated for current management conditions until a steady state was obtained. The Banatica plantation had an organic matter stock of 169 t SOM/ha and an annual input of 11.4 t crop residues (dry weight). As a result, the ratio *Min/Hum* equals 0.067. The San Pablo plantation had an organic matter stock of 108 t SOM/ha and an annual input of 14.6 t crop residues (dry weight). As a result, the ratio *Min/Hum* equals 0.134. The differences can be explained by differences in soil texture, but certainly also by the volcanic character of the soils in the Banatica plantation. Following the intentions to use banana stems for fibre production would result in a decrease in organic matter input of 4.7 t/ha in Banatica and 7.6 t/ha in San Pablo. This would result in a SOM decline of 50% eventually if the organic matter input is not compensated by, for example, organic fertilizers or green manure.

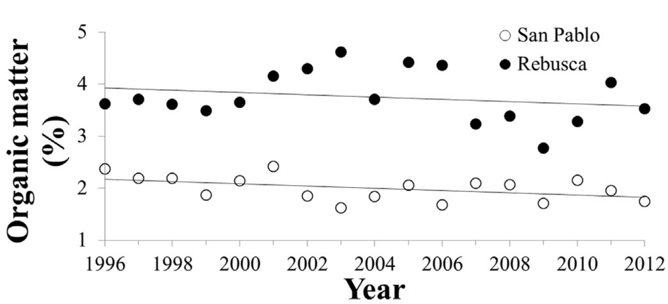

Fig. 4. Long-term (1996–2012) data on soil organic matter contents in two Costa Rican banana plantations in San Pablo (sedimentary soils) and La Rebusca (volcanic soils) were measured annually at the end of the year.

3.3. Discussion

This study illustrated the added value legacy data can have in a local study. Long-term field experiments were avoided by combining legacy data with the collection of new soil data. Data on SOM dynamics and the processes that influence the SOM content are available from legacy data sources (Shibu et al., 2006). Legacy data enriched the soil data for this local study. Modelling can play an important role in the analysis. On one hand, literature and models lacked basic knowledge on the banana production system. Therefore, it was impossible to carry out the data analysis without new data collection. On the other hand, some model parameters were impossible to collect in the field, due to time restrictions, and were therefore obtained from literature or long-term legacy data.

4. Exploring the use of field data in regional studies

The literature review showed that the number of studies that rely entirely on legacy soil data increased over time. Soil datasets can differ significantly from each other and this can affect the results of a study (Hendriks et al., 2016). Therefore, it is not recommendable to only rely on legacy data. This case study aims to explore and analyse how new soil data collection can enrich a regional study. This study analyses the effect Climate-Smart Agricultural (CSA) practices can have on potential rain-fed maize yields under future climate scenarios.

4.1. Introduction

Between 1981 and 2002, maize yields declined globally due to climate change and land degradation (Lobell and Field, 2007). The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) promotes the adoption of CSA practices through applying, e.g., terracing, stone bunds, dams, intercropping with legumes, integrated soil fertility management (www.ccafs.cgiar.org/flagships/climate-smart-technologies-and-practices). These CSA practices aim to sustainably increase productivity, adapt and build resilience to climate change, and reduce greenhouse gas emissions. Different studies demonstrated that CSA practices increased the productivity under current climate conditions (Paustian et al., 2016). However, it is highly uncertain whether this increased productivity withstands under changing climatic conditions. The CCAFS project puts a lot of effort in climate change adaptation and mitigation and therefore they want to know whether CSA practices can sustain productivity increases for the future.

4.2. Research implementation

The study is carried out in semi-arid Machakos and Makueni counties (Kenya) and covers approximately 8000 km^2. The climate scenarios were modelled using daily weather data of Machakos and Makueni counties from 2004 till 2012. For the short rainy season (Oct-Dec), a year with an average amount of rainfall (205 mm), a wet year (407 mm) and a dry year (131 mm) were selected. For these three years, four climate scenarios (RCP2.6, 4.5, 6.0, 8.5) were derived from WorldClim Version 1.4 (www.worldclim.org/version2). The methodology on how these scenarios were derived is described by Hijmans et al. (2005). The soils in the area were formed in the Basement System and resulted in deep and friable soils. Most dominant soil types in the study area are the ultic Haplustalfs, oxic Paleustults and rhodic Paleustalfs (Soil and Terrain database for Kenya (KenSOTER) V.2.0; Dijkshoorn, 2007). In the region, intercropping and terracing are already widely adopted as CSA practices (Tiffen et al., 1994).

The effect of CSA practices under different climate scenarios can be analysed in different ways. For example, one can use a crop-growth simulation model (e.g., Challinor et al., 2018) or one can do a field experiment that compares fields that did and did not implement CSA practices (Atreya et al., 2006). For this study, crop-growth simulation model World Food Studies (WOFOST) (Control Centre version 2.1; Boogaard et al., 2013) was used for the analyses. This decision made it possible to analyse a wide range of climate scenarios. The crop-growth simulation model requires soil data on water holding capacity (WHC), the runoff factor and the maximum rooting depth. The specific research question cannot be answered when only legacy soil data are used, because legacy data do not distinguish between different land management practices. However, it is resource consuming to collect data on the WHC, run-off factor and the maximum rooting depth. For Kenya, data on the WHC is available from the Fertilizer Use Recommendation Project (FURP, 1987; FURP, 1994), but this dataset does not distinguish between areas that did implement CSA practices and areas that did not. Having considered all options, we decided to use a pedotransfer function that derives the WHC based on sand, clay and organic matter content (Saxton and Rawls, 2006). These soil properties are collected using proximal sensors. Data on the runoff factor were obtained from drainage class and slope. Drainage class was selected from the KenSOTER database and slope was measured in the field where the soil samples were taken. The slope of individual farming fields could not be obtained from auxiliary information, such as the Digital Elevation Model. Terraced fields have a slope of 0°.

We point out the decisions that were made in order to obtain the required soil data, by evaluating the potential of both: the use of legacy data and the collection of new soil data.

Legacy data that was used:

- General information on the study area and the farming systems was obtained from the Fertilizer Use Recommendation Project (FURP, 1987; FURP, 1994). The project carried out intensive agronomic experiments and collected data on the land use and land management, described representative soil profiles that were under maize cultivation (including physical and chemical analyses), and analysed crop responses related to soil characteristics.
- Data on maximum rooting depth was obtained from the dataset of Leenaars et al. (2018), unless the maximum rooting depth for maize in Sub-Saharan Africa is reached. This depth is assumed to be 100 cm (Wolf et al., 2015). These data are used as input data for the crop-growth simulation model.
- A literature review combined the data on drainage class and slope into a quantitative value on the surface run-off (Rockström et al., 1999; Hoogmoed and Stroosnijder, 1984; Hoogmoed et al., 1991; Omoro and Nair, 1993; Kariaga, 2004; Ni-Meister, 2008).

New data that was collected:

- In total, 11 pairs were sampled to compare the effect of terracing and 13 pairs were sampled to compare the effect of intercropping on water-limited maize yield. These samples were collected between October and December 2013. All variables were kept the same, except that one field in the pair did not adapt the CSA practice and the other field did. A composite sample of the topsoil (0–20 cm) and a single sample of the subsoil (50–60 cm) were taken.

Table 1
Four climate scenarios to test the effect of terracing and intercropping on water-limited maize yield during a dry, an average and a wet cropping season.

	Precipitation (mm/season)	Mean min. T (°C)	Mean max. T (°C)	Effect of terracing (%)	Effect of intercropping (%)
Dry season	131	20.5	28.0	50.4	2.0
CS 1	136	22.1	28.6	9.7	−1.6
CS 2	148	22.5	29.3	8.5	0.0
CS3	159	22.5	28.9	8.4	0.6
CS4	97	23.2	29.5	13.7	−3.0
Average season	205	18.2	27.9	4.0	1.7
CS 1	220	19.6	28.6	4.0	0.5
CS 2	204	20.0	29.2	1.0	−0.2
CS3	240	20.0	28.9	2.1	1.3
CS4	179	20.6	29.4	3.0	−1.7
Wet season	407	18.5	28.2	3.8	0.9
CS 1	645	20.0	28.9	−0.6	−1.2
CS 2	464	20.3	29.6	0.0	0.1
CS3	484	20.3	29.2	0.0	0.2
CS4	392	20.9	29.7	0.0	0.0

- Stoniness can reduce the WHC. These data were not available from legacy soil data and therefore data on the stoniness were collected in the sampled field.
- Data on land use, land use history and land management were collected in the fields where the soil samples were taken. These data were used to check the comparability of the paired samples.

The results showed that terracing did not directly result in an increase in SOM content (−0.1%) and finer soil textures (−1.6%) as expected. This can be caused by the soil displacement from topsoil and subsoil when terraces were made. Intercropping resulted in a slight increase in SOM content (0.1%) and finer soil textures (1.3%). Differences between terraced and non-terraced fields and between intercropped and mono-cropped fields were analysed. The effects of terracing and intercropping on potential water-limited maize yields were simulated for three different years and four climate scenarios (Table 1). Terracing seems to be a suitable CSA practice as potential maize yields increased significantly ($P < 0.05$) under almost all future climate scenarios, except for the wet year. This is caused by the soil and water conservation aspects of terracing in drier and average seasons. Intercropping, on the other hand, did not significantly increase the simulated water-limited maize yields. This is because the potential beneficial effect of intercropping on soil nutrients (N fixation) is not reflected in the simulated water-limited maize yield.

4.3. Discussion

Soil data on different land management practices could not be obtained from the legacy soil data that were available for this study area. Collecting these supplementary data made it possible to study the effect of CSA practices at regional scale. The effect of CSA practices has often been studied on individual farms. However, policies and governmental programs operate for a large group of farms or for a region (Smit et al., 1996), which makes it essential to frame studies on CSA practices in a wider context. A good example is the study of Saiz et al. (2016), where new soil data were combined with the World Reference Base (IUSS Working Group WRB, 2015) to assess the long-term impact of Fanya-juu terracing on SOM-related properties. Complex soil property data on the water retention parameters could be obtained at regional scale by making use of a pedotransfer function. This function only required simple soil characteristics as input data. These data can more easily be collected and analysed in the laboratory or by proximal sensors compared to the water retention parameters.

5. General discussion

5.1. Reduce sampling effort

New soil data collection does not necessarily need to be expensive and time-consuming. The case studies illustrated that the sampling effort can be reduced by making use of auxiliary data, proximal sensors, soil models, pedotransfer functions and legacy soil data. After reviewing 120 studies, we can conclude that there were quite some studies that could have reduced their sampling effort by making better use of available tools and techniques. For example, Shirani et al. (2015) aimed to obtain insight in the spatial variation of an area in Iran and chose for a grid sampling strategy without considering any legacy soil data or auxiliary information. The number of soil observations could probably be reduced and the observations could have been taken at 'smarter' locations, e.g., at locations where soil variability was expected to be highest, when legacy soil data and auxiliary data were used. Conventional soil surveys required 1 to 4 observations per cm^2 on the final map (Steur, 1961), while updating the 1:50,000 soil map of a 2680km^2 area only required 150 additional soil observations (Kempen et al., 2009).

Laboratory costs can be reduced by making use of proximal sensors or pedotransfer functions. Proximal sensors can collect a large number of soil observations. Only few soil samples need to be send to the laboratory for checking the quality of the proximal sensor. Pedotransfer functions often require simple soil characteristics to estimate a complex soil property. For example, some pedotransfer functions that estimate the water retention parameters only require data on soil texture and organic matter content. These data can easily be collected and analysed in the laboratory.

The first case study made use of a dynamic soil organic matter model that could predict the change in soil organic matter content over time. Making use of computer models can reduce the time spend on field experiments. Keeping in mind that statistical or dynamic soil models only reflect a simplification of reality, several studies use soil models for their land use analysis (e.g., Knorr et al., 2005; Cooley et al., 2005; Gessesse et al., 2014).

5.2. Facilitate legacy soil data

The literature review showed that the total number of studies that relied entirely on legacy soil data increased and that especially regional studies increasingly use legacy soil data for their analysis. This trend is confirmed by Hartemink et al. (2001). In the study of Hartemink et al. (2001) the number of studies that collected new soil data decreased from 29% to 18% between 1970 and 1990. Studies that use legacy soil data still dominantly rely on conventional soil data. When these soil data are used, they should be accompanied by new soil data to verify the applicability of the data source for a specific study. Soil scientists can help facilitating soil data acquisition by: (i) making new soil data products meet the soil data requirements and (ii) make soil data products freely available through soil data portals or soil data warehouses (e.g., Soil Survey Division Staff, 2017). In these warehouses, customers can choose an area of interest, browse and select required soil data, customizing the format, reviewing the usage and quality of the soil data and downloading the data. They ease the identification of missing data and improve the access to the required soil data.

5.3. Combining new and legacy soil data

There are two key requirements for combining legacy and new data: (i) legacy soil data need to be available and (ii) resources to collect new soil data need to be available. For the two case studies, both requirements were met. The local case study took advantage of legacy soil data by using legacy data on the mineralization rate. Collecting these data in the field would have been too expensive and time-consuming. The regional case study enriched the available legacy soil data by collecting new soil data at different land management. The stoniness of a soil was also measured in the field, because these data can significantly reduce the water holding capacity (Antwi-Agyei et al., 2012). We realize that not all studies are able to combine new and legacy soil data. In a study of Jackson (2015), for example, it was impossible to combine legacy soil data and new soil data due to a lack in legacy soil data. Another example is the study of Wilford et al. (2015), where it was unnecessary to combine legacy and new soil data. For this study, the required soil data could be obtained at the required level of detail from the National Geochemical Survey of Australia (NGSA; De Caritat and Cooper, 2011). The literature review did not reveal any local studies that did not collect new soil data. This can, for example, be caused by the lack in legacy soil data at detailed scale or the lack in searching for other soil data sources than conventional soil maps. Legacy soil data still contain valuable quantitative and qualitative information that should not be neglected. Even when legacy soil data do not directly meet the soil data requirements anymore, these data can help designing the sampling scheme, provide information on the soil profile and provide information on most important soil forming processes in the area. Several studies have successfully shown that the soil data can be enriched by combining legacy and new soil data. For example, outdated legacy soil data can be updated by collecting a limited number of additional soil data in combination with digital soil mapping techniques (Kempen et al., 2009; Yang et al., 2011). Another example is the study of Pelegrino et al. (2016). In this study the prediction of soil classes improved because additional soil data was collected in the areas of high uncertainty.

6. Conclusions

This study concludes that: (i) studies still often collect new soil data, while the availability of legacy soil data increased over recent decades, (ii) studies that use legacy soil data mainly use conventional soil maps despite their limitations, and (iii) new tools and techniques for soil data acquisition became available, but still many of the reviewed studies that collected new soil data could reduce their sampling effort. These contradictions ask for a change in the balance between the use of legacy soil data and the collection of new soil data. Legacy soil data can improve new soil data collection and new soil data can reduce the limitations of the legacy data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2019.04.026.

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