How to feed environmental studies with soil information to address SDG 'Zero hunger'

Chantal Hendriks, Jetse Stoorvogel, Lieven Claessens

Lighthouse examples

Discussion

Conclusion

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To reach SDG 2 “Zero Hunger”, food production needs to increase. Crop-growth simulation models are commonly used to explore the potential increase and evaluate alternative management strategies. To apply these models, soil data are required. Because the soil data requirements changed over recent decades, legacy soil data often do not meet the requirements. (1/3)

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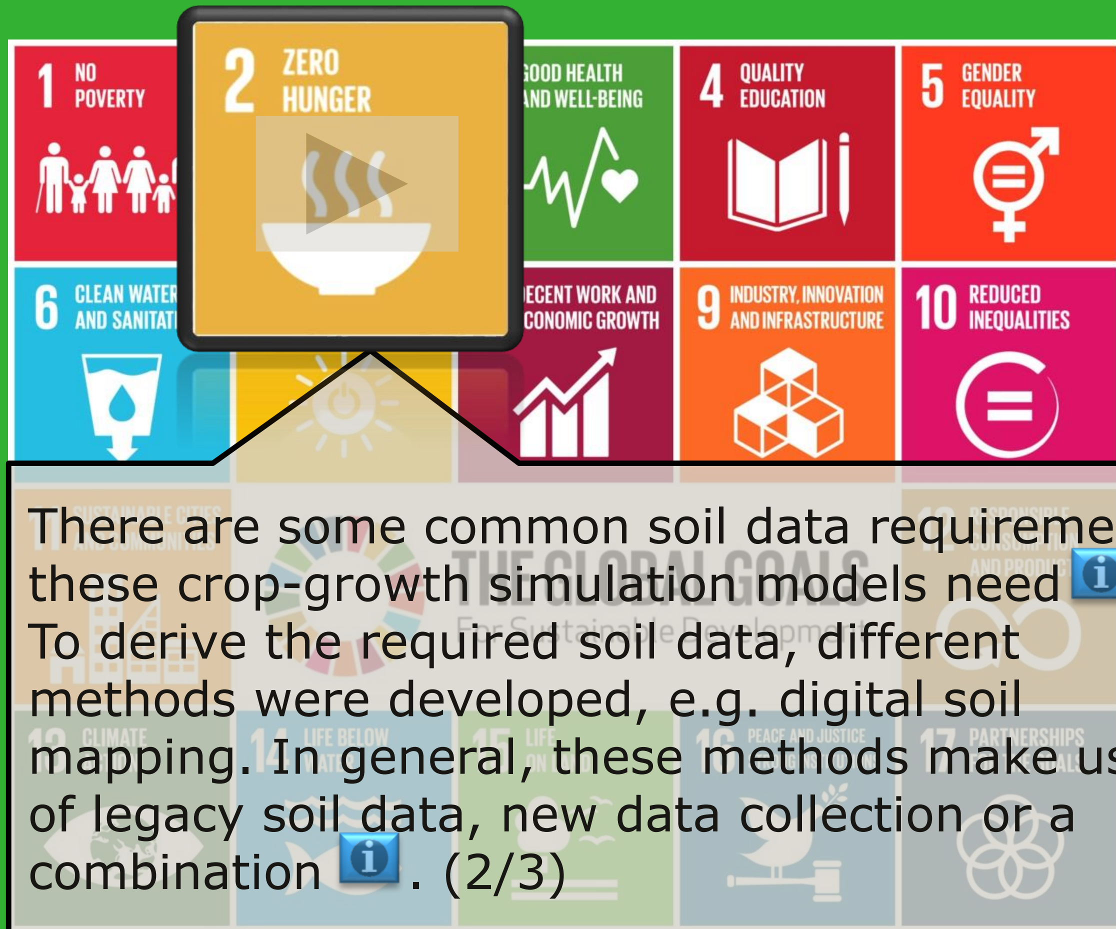

There are some common soil data requirements these crop-growth simulation models need . To derive the required soil data, different methods were developed, e.g. digital soil mapping. In general, these methods make use of legacy soil data, new data collection or a combination . (2/3)

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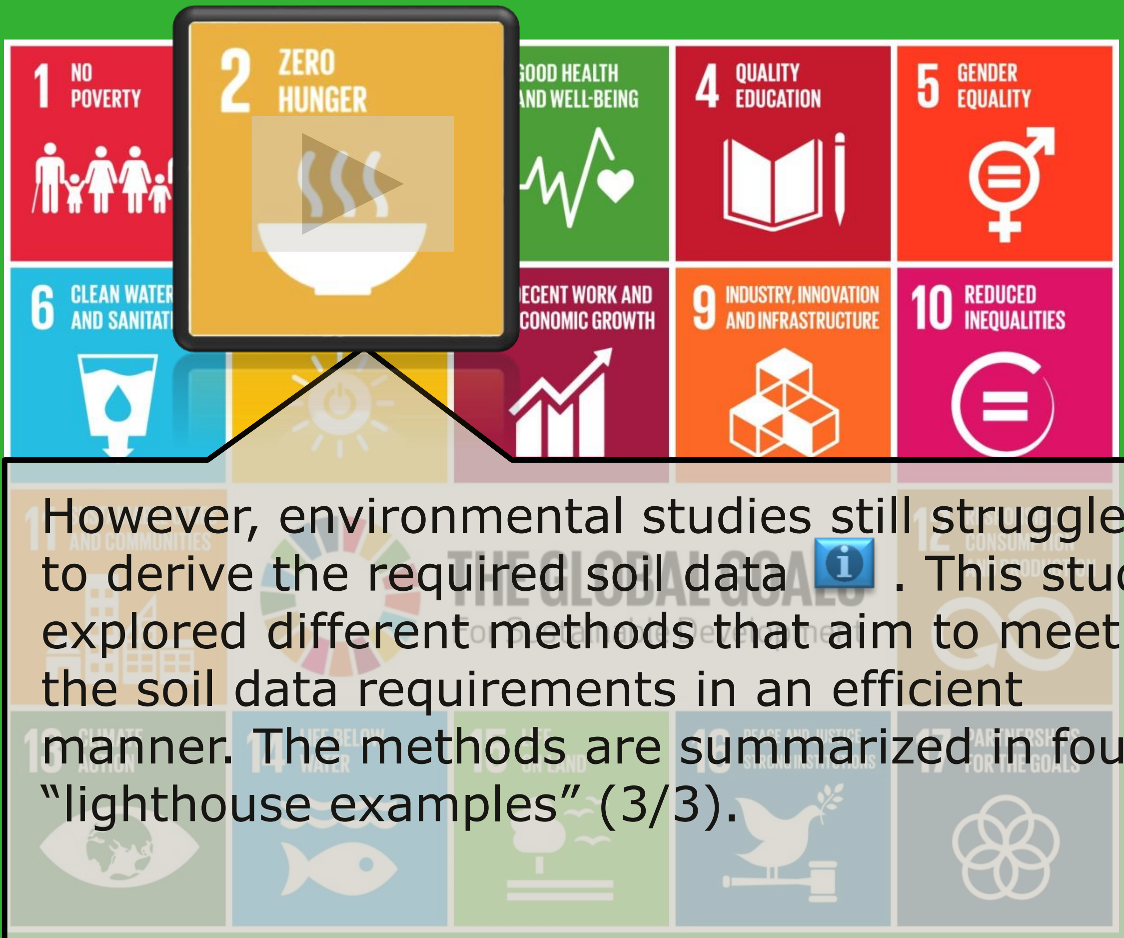

However, environmental studies still struggle to derive the required soil data . This study explored different methods that aim to meet the soil data requirements in an efficient manner. The methods are summarized in four “lighthouse examples” (3/3).

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Need for different methods to meet soil data requirements

Lighthouse example 1:
'Mechanistic digital soil mapping'

Lighthouse example 2:
'Legacy soil data specifically developed for yield gap analysis'

Lighthouse example 3:
'Collecting new soil data to predict complex soil properties'

Lighthouse example 4:
'Deriving additional soil data for highly variable topsoil'

Mechanistic digital soil mapping

This study explores the possibility to predict soil organic matter (SOM) contents using process-based relationships. This mechanistic way of mapping is explored in a nature area in Spain (Cantabria region) and can further be developed for agricultural areas.

This nature area is assumed to be in equilibrium, therefore:

$$SOM_{in} = SOM_{out}$$

Lighthouse example 1
Mechanistic soil mapping

Lighthouse example 2
Deriving soil data using legacy soil data

Lighthouse example 3
Deriving soil data collecting new soil data

Lighthouse example 4
Deriving soil data from a combination of legacy and new soil data

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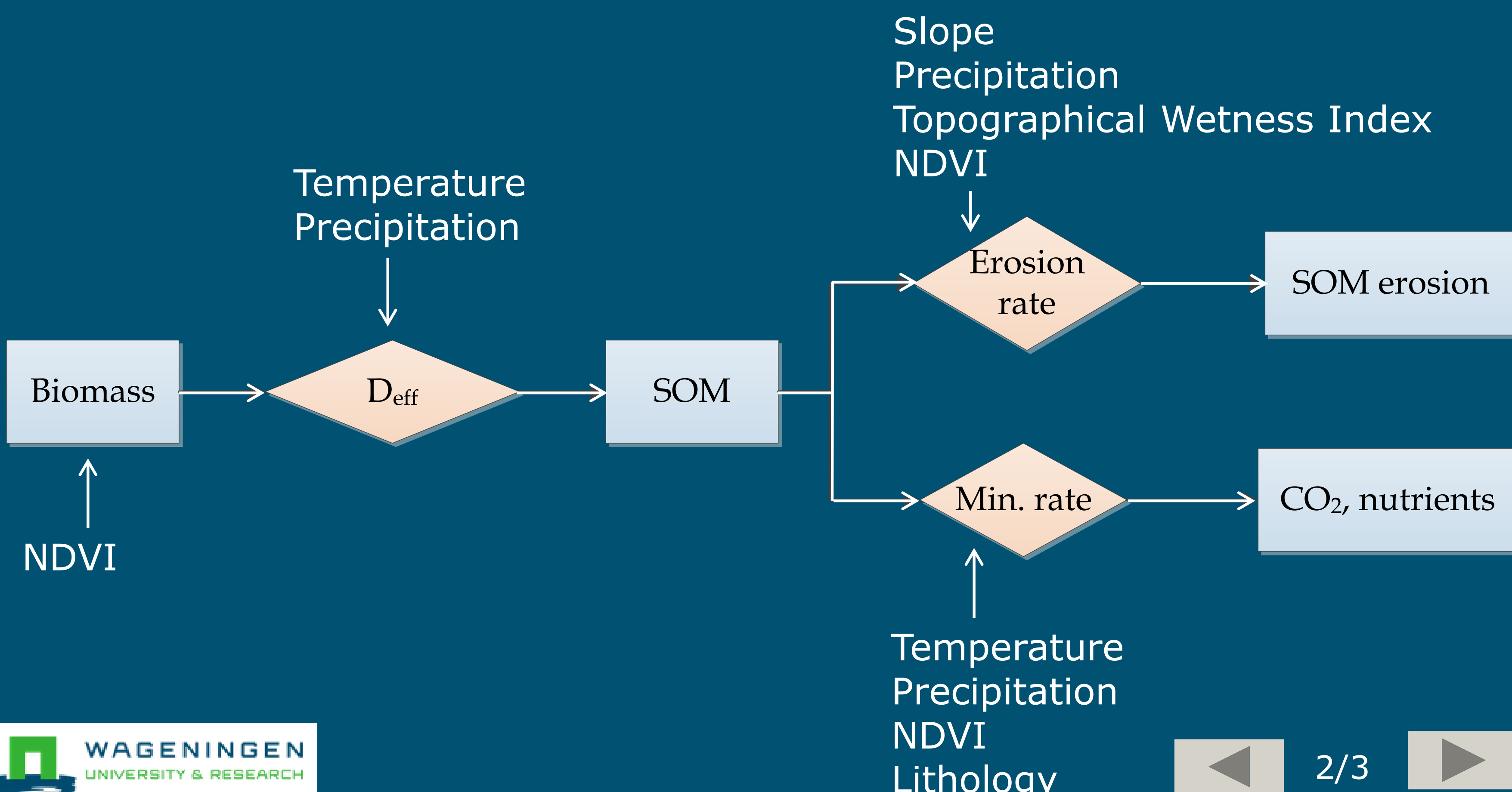
Mechanistic digital soil mapping

Each process can be explained by one or several environmental variables.



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Mechanistic digital soil mapping

Strenghts

S1. On extremes this way of mapping gives realistic values.

S2. Extrapolation to similar nature areas is possible.

S3. Mechanistic processes behind soil formation are taken into account.

Weaknesses

W1. We assume that the nature area is in equilibrium.

W2. The method depends on the availability of environmental variables.

Opportunities

O1. Environmental variables that better explain stoniness become available. Stoniness has a large effect on predicting the SOM content.

O2. Validate the model.

O3. The availability or resolution of environmental variables increases.

Threats

T1. Statistical models can predict better on extremes then mechanistic models.

T2. Statistical models can better extrapolate soil properties then mechanistic model.

T3. The environmental variables that are required to predict the mechanistic process are not available.

Legacy soil data specifically developed for yield gap analysis

The Global Yield Gap Atlas project used a bottom-up approach to estimate the difference between potential or water-limited yield and actual yield.

In this study the yield gap for Machakos-Makueni counties (Kenya) was estimated. Due to the global character of the project, soil data needed to be available from legacy soil data sources.

The project faced several problems with the soil data sources for Africa, and therefore a functional soil dataset that included several complex soil property maps was specifically developed for this project; the AfSIS-GYGA dataset.

Lighthouse example 1
Mechanistic soil mapping

Lighthouse example 2
Deriving soil data
using legacy soil data

Lighthouse example 3
Deriving soil data
collecting new soil data

Lighthouse example 4
Deriving soil data from a
combination of legacy and
new soil data

1/3

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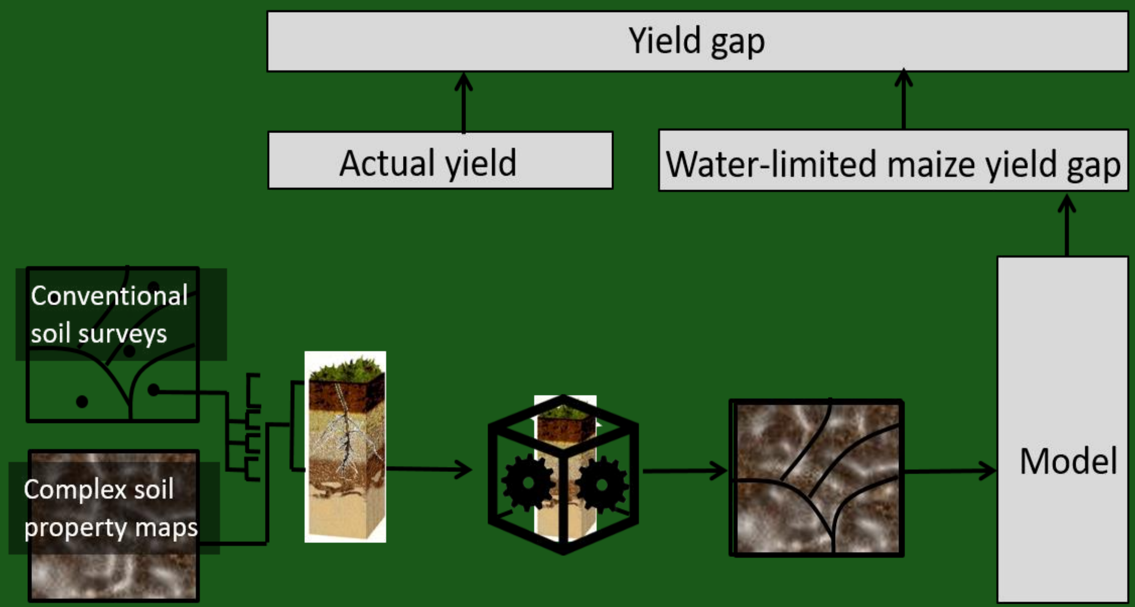
Legacy soil data specifically developed for yield gap analysis

For this example a slightly different crop-growth simulation model was used and therefore the model required besides the complex soil property maps of AfSIS-GYGA, some other soil properties using a conventional soil surveys.



Legacy soil data specifically developed for yield gap analysis

Strengths

S1. The soil data requirements are met.
S2. Collecting new soil data is not required.
S3. Only few functional soil property maps were required for the model.
S4. The method includes variation over depth by taking depth weighted averages of the root-zone depth.

Weaknesses

W1. Legacy soil datasets were established using assumptions. These assumptions have influence on the value of the soil properties.
W2. The uncertainty increases when legacy soil datasets are used to develop a new legacy soil dataset.
W3. Variation over depth is aggregated, because depth weighted averages of the root-zone depth were taken.

Opportunities

O1. Legacy soil data are validated.
O2. Transparency about the effect of assumptions on soil property values.
O3. Legacy soil datasets were established with the aim to serve SDPs. These datasets provide quantitative, spatially exhaustive soil data that include variation over depth.

Threats

T1. The legacy soil dataset(s) used to develop the new legacy soil dataset is of poor quality.
T2. The SDP focusses on an area where no legacy soil data are available.
T3. The legacy soil dataset does not provide the required soil data for the model, e.g. information on different land management.

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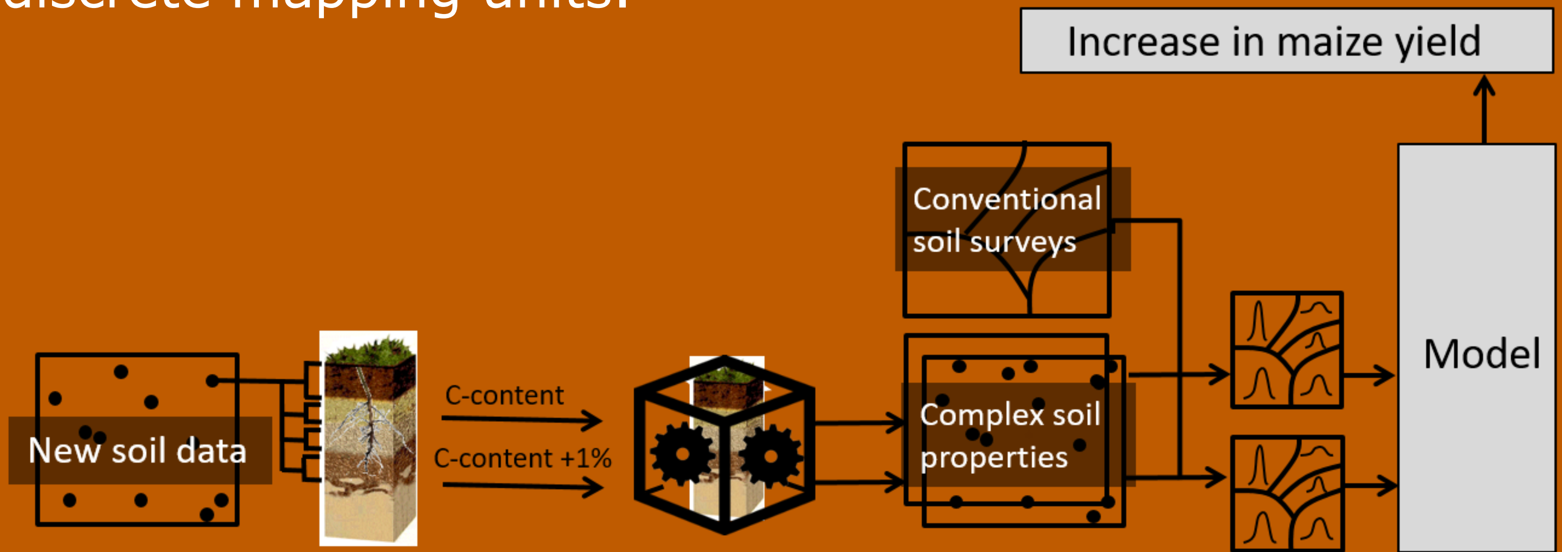
Collecting new soil data to predict complex soil properties

To estimate the effect of agroforestry on maize yield in the Lower Nyando Basin (Kenya), the Climate Change, Agriculture and Food Security (CCAFS) project requested to provide soil data.

The area is only 100 km^2 and therefore legacy soil data do not meet the required level of detail. New soil data of each soil horizon were collected. These data were used to define functional soil properties on the water holding capacity and the nitrogen availability; most important complex soil properties for crop growth.

Collecting new soil data to predict complex soil properties

Soil data of the soil profile were collected. Complex soil properties were derived from basic soil properties using conversion factors and pedotransfer functions. Due to high short distance variation it was not recommendable to map the complex soil properties spatially continuous. Therefore, we described the variation within within discrete mapping units.



Collecting new soil data to predict complex soil properties

Strengths

S1. The method includes variation over depth by taking depth weighted averages of the soil profile.

S2. Complex soil properties are interpretable by users outside the soil science community.

S3. The number of model parameters is reduced because we estimated complex soil properties rather than basic soil properties.

S4. Complex soil properties consider correlations between basic soil properties.

Weaknesses

W1. The method is crop specific. The number of maps increases when a study requires information on different crops.

W2. It is difficult to trace back which basic soil property influences the results and the quality of the resulting map most, because of the integrated character of complex soil properties.

W3. Pedotransfer functions or default values are required to derive complex soil properties.

Opportunities

O1. The regression model can improve when different environmental variables become available.

O2. The availability of proximal sensors can increase the number of soil observations.

O3. The estimation of complex soil properties can improve when pedotransfer functions improve and when complex soil properties can be validated.

Threats

T1. Spatial variation takes place on short distances, which makes it difficult to predict the spatial variation.

T2. Complex soil properties cannot be explained by linear models.

T3. The free access of soil data and environmental variables becomes stricter.

Deriving additional soil data for highly variable topsoil

To analyse the trade-off between poverty and soil fertility, the production potential of maize was estimated for Machakos and Makueni counties (Kenya).

Different legacy soil data were available for the counties, but the values of the soil properties differed between the datasets.

Besides that, most legacy soil data were only available on a course scale. The topsoil of agricultural soils are in general more variable that the subsoil. Therefore, additional soil data on the topsoil were collected.

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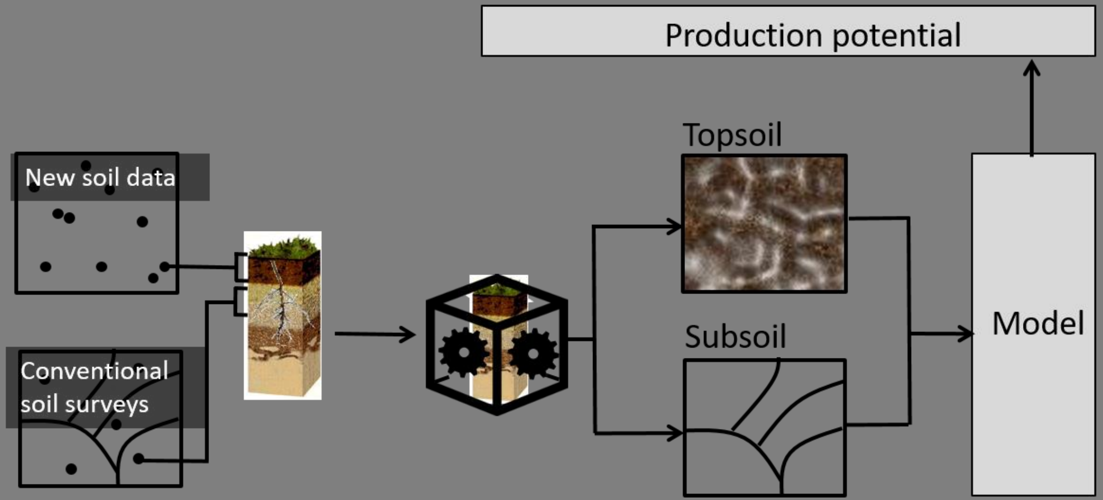
Deriving additional soil data for highly variable topsoil

Additional soil data on the topsoil were collected. The map was analyzed using regression kriging, one of the most common methods in digital soil mapping. This resulted in a spatially continuous map of the topsoil. For the subsoil the mapping units and the most representative soil profiles were used.



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Deriving additional soil data for highly variable topsoil

Strengths

S1. The collection of additional soil data helped to predict the spatial variation of the topsoil in more detail.

S2. Variation over depth is included by also providing subsoil data using legacy soil data.

Weaknesses

W1. There is assumed that the subsoil is less variable and not related to land use.

W2. The depth intervals were fixed, which means that variation within the fixed layer was ignored.

W3. The correlation between clay and SOM content is ignored by mapping basic soil properties individually.

Opportunities

O1. The additional soil data collected can be used for multiple purposes, e.g. for checking the quality or updating legacy soil data.

O2. The statistical model that are used to map the topsoil improved (e.g. due to the availability of different or improved environmental variables).

O3. The availability of proximal sensors increases the number of soil observations.

Threats

T1. The spatial variation that is provided by the legacy soil dataset is not representative.

T2. It is not possible to apply the available pedotransfer functions to the study area.

Soil data sources

Soil data are derived from

Legacy soil data | Combination | New soil data

Soil data sources

Soil data are derived from

Legacy soil data	Combination	New soil data

Globally, the availability and the scale level of legacy soil data differ. Conventional soil surveys are the most common data source. Other sources include digital soil maps, point observations, and remotely sensed soil data. Legacy soil data differ in the type of data (qualitative vs. quantitative), the description of spatial variation (spatially continuous or discrete mapping units), the description of the soil profile (full soil profile or average data on the topsoil). Literature mentions a number of potential limitations of legacy soil data. They may be:

- outdated,
- qualitative,
- not spatially continuous,
- at a coarse scale,
- inconsistent, or
- lacking a quality assessment.

Soil data sources

Soil data are derived from

Legacy soil data | Combination | New soil data

We compared different legacy soil datasets for an area in Kenya (Machakos and Makueni counties). The values between the soil properties differ considerably between datasets.

Averages and standard deviations (in brackets) of four soil properties for six soil datasets.

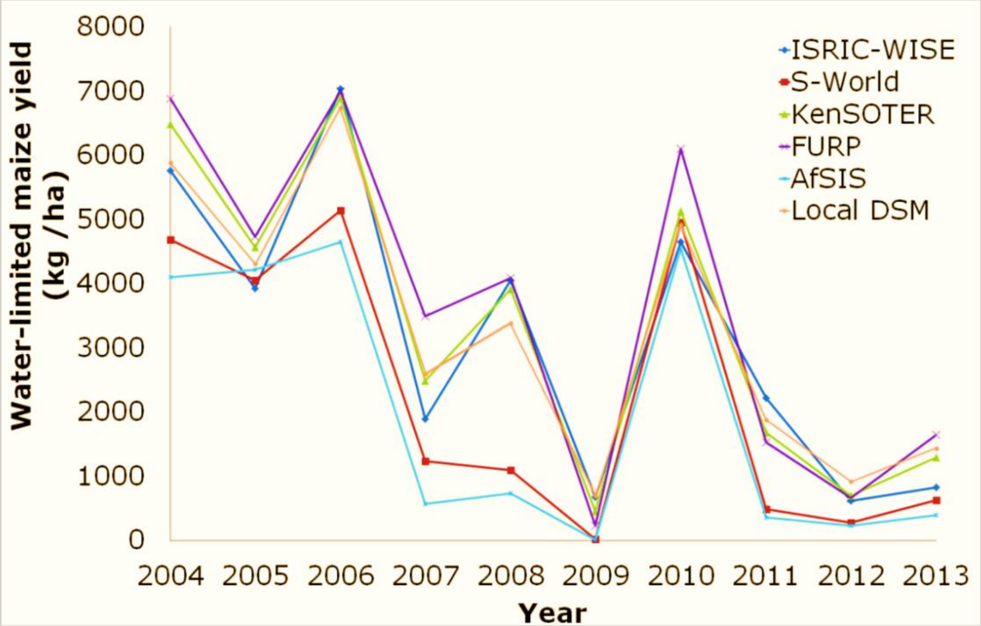
Soil dataset	**Carbon (%)**	**Sand (%)**	**Clay (%)**	**pH (-)**
ISRIC-WISE	0.6 (0.1)	43.5 (6.5)	37.7 (4.1)	6.2 (0.7)
S-World	1.5 (1.2)	45.1 (16.5)	36.9 (13.4)	6.2 (0.4)
AfSIS	0.4 (0.2)	13.6 (6.1)	8.3 (2.9)	4.7 (0.4)
Local DSM	0.8 (0.2)	71.7 (17.6)	23.6 (8.8)	n.a.
KenSOTER	1.0 (0.6)	48.0 (21.0)	31.8 (16.7)	6.1 (1.1)
FURP	0.3 (0.0)	36.2 (5.0)	44.4 (7.2)	5.1 (0.7)

Soil data sources

Soil data are derived from

Legacy soil data | Combination | New soil data

The differences between soil datasets resulted in major differences in simulated water-limited maize yields, although the differences differed between years (e.g., >3 ton/ha difference in 2007-2008 and <1 ton/ha in 2005 and 2009)



Hendriks et al., 2016

Soil data sources

Soil data are derived from

Legacy soil data	Combination	New soil data

Collecting new soil data is often seen as expensive and time-consuming. Conventional soil surveys required intensive sampling. The development of Digital Soil Mapping (DSM) techniques reduced the number of soil observations to predict soil properties. However, crop-growth simulation models require data on the entire soil profile which may require complex three-dimensional (3D) DSM techniques. For these techniques the number of required soil observations increases again.

Soil data sources

Soil data are derived from

Legacy soil data	Combination	New soil data

Soil data for environmental studies can be enriched when legacy soil data and new soil data are combined.

Legacy soil data can for example:

- Provide additional soil observation and insight in temporal or spatial variability
- Provide insight in the expected soil variation
- Stratify the area
- Provide information on soil forming processes

New soil data can for example:

- Fill up missing data in the legacy data
- Validate and verify legacy data
- Check assumptions

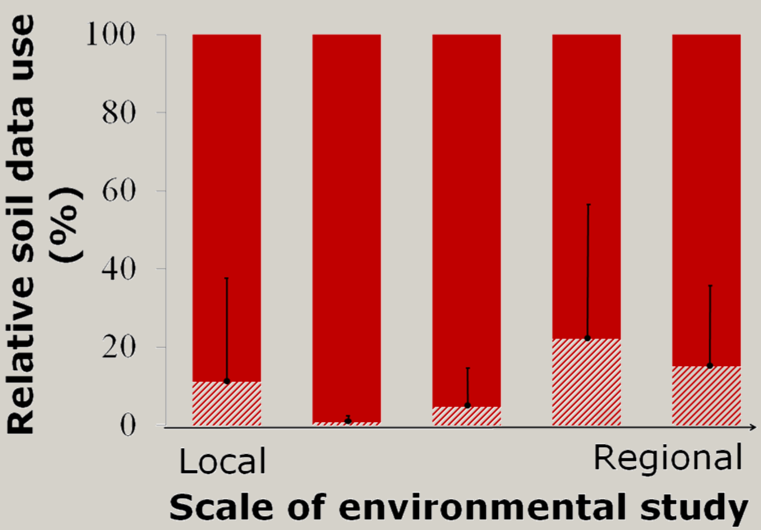
Soil data sources

Soil data are derived from

Legacy soil data | Combination | New soil data

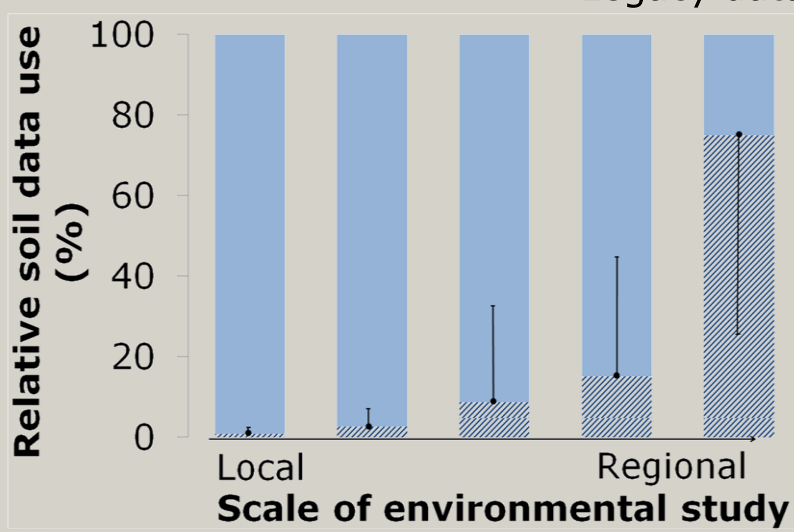
The relative use of legacy soil data and collecting new soil data was analysed. In a literature study, Geoderma papers published between 1967-1971 and between 2015-2016 were analysed:

1967-1971



2015-2016

■ New data
▨ Legacy data



Soil data requirements

Crop-growth simulation models typically require

- Quantitative (basic or complex) soil information
- Soil information on the spatial variation
- Soil profile information on the variation over the root-zone
- A specific level of detail at which the soil data are provided
- Validated soil datasets

Problems with deriving the required soil data for environmental studies

The soil data are:

- Not available at the required level of detail.
- Only provide data on the topsoil.
- The soil dataset are not validated.
- Individually modelled soil property maps.
- Described in discrete mapping units that can include more soil types. The location of a soil type within a mapping unit is unknown when more soil types are described within a mapping unit.

The methods for soil data acquisition:

- require many soil observations.
- are complex and therefore difficult to interpret.
- use statistical models to predict soil properties that were formed by mechanistic processes.

Discussion

- Relative simple methods can already solve some of the problems that are faced with soil data in environmental studies.
- Legacy soil data and new soil data should more often be combined in environmental studies that aim to address SDGs.
- Functional soil information better meet the soil data requirements, but crop-growth simulation models still require basic soil properties. Adaptation is required.
- The efficiency of a method depends on (i) the use of legacy soil data and environmental variables, (ii) the collection of the required soil data, and (iii) the methods used to derive soil data.

Recommendations

Recommendations

Tick boxes that are essential to feed environmental models with soil information to address SDG "Zero Hunger":

- ❑ Is there legacy soil data available
- ❑ Are these data quantitative
- ❑ Do these data provide information on the spatial variation
- ❑ Are these data on the required scale
- ❑ Do these data include variation over depth
- ❑ Are these data validated
- ❑ Is the quality of the datasets satisfactory

If one or more tick boxes cannot be checked: collect additional soil data that specifically aims to derive the data for the tick box(es).

Additional soil data cannot be collected: search for different legacy soil data sources. Compare, combine and analyse the differences.

Conclusions

- Soil scientists can provide the required soil data for SDGs.
- Transparent methods are available to address SDG “Zero Hunger” and can in many cases replace complex (3-D) digital soil mapping techniques.
- Despite studies on food security differ, there are some common soil data requirements.
- Functional soil data need to be established.
- Validate established soil datasets.

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