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Can global soil organic carbon maps be used in policy decisions on practical agricultural management?

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Abstract

Decreasing soil fertility – with insufficient soil organic carbon (SOC) content being a key driver/indicator – pose major limitations to crop growth and food security. Improved agricultural soil management will have two mutual benefits: increased soil fertility and (possibly) climate change mitigation. The challenges related to management of the SOC pool are global, the policy is large-scale but any required actions are local and need to be site-specific in order to be efficient. For this, adequate decision support is needed but often lacking. There is a multitude of global efforts to derive such decision support in the form of digital soil maps/soil geodatabases of SOC. One should be aware that high spatial resolution and missing or questionable validation statistics not representative for the intended use can be misleading. The present study, exemplified with data from Rwanda, concludes that global SOC datasets should not be used as decision support for policymakers without prior validation in the area of interest. In case the dataset in question is not found adequate, downscaling/local adaptation through multiscale data fusion may be a viable option.

Keywords: Downscaling, Digital Soil Map; Rwanda; SoilGrids, Soil organic carbon; SOC sequestration; Validation; Water Land and Ecosystems (WLE).

Introduction, scope and main objectives

Digital soil mapping (DSM) is currently carried out in many parts of the world and at different scales, including continental and global scales (e.g. Arrouays et al. 2014; Hengl et al. 2016; Minasny and McBratney 2016; Stoorvogel et al. 2016). In essence, DSM aims at determining soil variation in relation to the landscape by finding measurable proxy variables for the soil property of interest and developing quantitative (spatial or non-spatial) models for prediction of the target soil property. Development of global and continental soil databases will change the manner in which soil data can be included in, for example, the decision-making processes in society at large e.g. by the FAO. Soil organic carbon (SOC) content is one of the most important indicators of soil condition. SOC stocks are currently a much discussed topic in both science and politics across a multitude of scales. O'Rourke et al. (2015) reviewed SOC stock science and policy and found that most scientific work is aimed at understanding the biophysical processes governing SOC content at small scales, from particles to landscapes, whereas policy work is predominantly aimed at larger (even global) scales. The authors concluded that attempts to characterise the greatest risks to SOC stocks require data spanning a number of scales and that science and policy need to be integrated across multiple scales. The overall aim of the present study was to assess the possibilities of utilising data from the global SoilGrids database of ISRIC (Hengl et al. 2016) at two different levels of relevance in the practical application of overall decisions on SOC soil management aiming at SOC sequestration and restoration of fertility – both at the farm level and at local administrative Sector units – exemplified with extensive ground truth data in Rwanda in central Africa. The full study was reported in Söderström et al. (2016).

Methodology

SoilGrids (ISRIC – World Soil Information, Wageningen) is currently the most detailed (in terms of spatial resolution; 250 × 250 m^2) global soil database. It includes predictions on SOC content as well as a number of other soil properties, e.g. texture, bulk density, pH and cation exchange capacity (CEC), at up to seven soil depths (0, 5, 15, 30, 60, 100 and 200 cm). The basis for the predictions in Africa is a set of about 28 000 soil observations distributed throughout the continent, combined with a set of covariates (Hengl et al. 2016). For the purposes of the present study, two independent datasets of agricultural land in Rwanda were compared with SOC data from SoilGrids to assess the usefulness of SoilGrids for SOC mapping at three scales: averages for country, sector administrative units, and smallholder farms.

All data used represented the SOC content in the topsoil. We used 800 soil analyses distributed over agricultural land in Rwanda (about 1.2 million ha) as the "ground truth". Each sample represented one smallholder farm of ~ 0.5-1.0 ha. In addition we had another independent reference dataset consisting of 100 soil analyses from similar smallholder farms randomly distributed over Rwanda.

Averages for the administrative sector units were judged as being a suitable working level from an advisory service perspective and also a potentially realistic unit size for use of the SoilGrids data. Administrative sectors are the third level of administrative subdivision in Rwanda. They differ in size, but on average they cover about 50 km^2. There were 392 sectors part of which was classified as agricultural land.

Regression kriging (Odeh et al. 1995) was used in order to investigate whether it was possible to apply a simple approach to locally adapt, or downscale, the SoilGrids SOC maps using a number of available local soil analyses. Comparisons between independent observations and predicted values in different types of maps were done to validate the different mapping methods. The coefficient of determination (r^2), which the correlation between map data and ground truth can be inferred and the mean absolute error (MAE), which is a measure of the error magnitude, were used for validation.

Results

Country average SOC

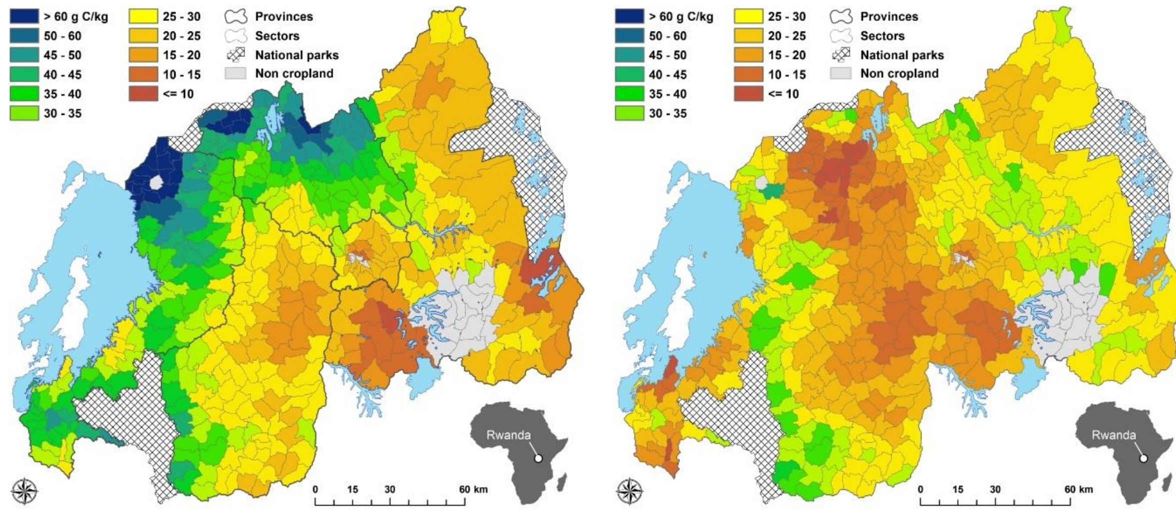
The average SOC content in agricultural soils of Rwanda according to SoilGrids was about 25% higher than that based on the ground truth soil dataset of 800 soil samples (31 compared with 25 g C kg^{-1}). The 100 reference samples randomly distributed in the country produced similar summary statistics as the full ground truth dataset. In other words, a national average based on 100 samples was in this case a more accurate option than an average based on the SoilGrids map.

Sector average SOC

Directly estimating SOC content for different administrative sectors using SoilGrids did not work very well either ($r^2 = 0.05$, MAE = 11g C kg^{-1}). Downscaling the SoilGrids data by regression kriging using the 100 reference soil analyses reduced the errors and augmented the correlation to the ground truth dataset of 800 samples ($r^2 = 0.33$ and MAE = 5 g C kg^{-1}).

Smallholder farm average SOC

Farm average SOC content was poorly correlated to the ground truth data ($r^2 = 0.05$; MAE = 13 g C kg^{-1}). Interpolation (ordinary kriging) using as few as 100 samples reduced the MAE by 50% (6.5 g C kg^{-1}). However, by applying the regression kriging approach for local adaptation and combining100 samples with the SoilGrids data an even lower MAE (6.1 g C kg−1) was achieved and a substantially higher r^2 (0.16 vs. 0.05). Using more samples further reduced MAE and elevated r^2.



a) b)

Fig. 1: Soil organic carbon (SOC) content in agricultural land in different administrative sectors of Rwanda. Sector averages of SOC content estimated from a) SoilGrids, b) Downscaling SoilGrids with 100 local soil samples using regression kriging. This procedure for local adaptation considerably improved the SoilGrids map (Söderström et al. 2016)

Discussion

Digital soil mapping has revolutionized the manner in which detailed maps of soil properties can be produced. By combining soil reference data with detailed data sets of auxiliary information in predictive modelling, maps of soil properties covering vast areas can be generated. From a non-experienced user's perspective, or indeed from the perspective of developers of guidelines and policies, it may be reasonable to believe that information derived from renowned research organizations can be trusted and applied. Defourny et al. (2012) reported that in many global land-cover applications, the quality and accuracy of the land-cover maps used are not considered. Instead, it is up to the potential user to assess whether the map is appropriate for the application. It has been reported that more than one-third of 90 DSM studies included in a review (Grunwald 2009) were not validated at all. In addition, validations can easily be misunderstood and misinterpreted since reported uncertainties heavily depend on the manner in which the validations were performed. We have shown that SOC in the topsoil as portrayed in the SoilGrids database was poorly correlated to independent extensive datasets covering the agricultural land of Rwanda ($r^2 = 0.05$; MAE 13 g C kg^{-1}). However, through combining a reasonably low number of local soil samples with the SoilGrids database it was possible to downscale the SoilGrid database to perform better. The same approach was tested also in other areas in western Kenya and northern Namibia and the results (to be published) follow the same trend.

Conclusions

We conclude that use of global soil databases on SOC should not be applied for regional or local estimates without any reference samples with which to compare. High spatial resolution in a continental data set can be misleading; it is normally only the framework upon which the predictions are made, rather than the resolution of potential applications. In order to prevent inadvertent misuse of published soil data, the DSM community must help users assess whether the map data are appropriate for their intended use. Validations should challenge the predictions – this is unfortunately often not the case. If a large-extent map is found to be too coarse for a specific application (e.g. estimates of SOC sequestration), downscaling and local adaptation may be possible if a number of additional soil observations are available. We recommend further studies on approaches for local improvement of global and continental data sets and call for innovative ideas on how map uncertainties can be made accessible and understandable to general users.

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