GLOBAL SYMPOSIUM ON SOIL ORGANIC CARBON, Rome, Italy, 21-23 March 2017

Global Space-Time Soil Organic Carbon Assessment

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Abstract

We mapped how soil carbon changes with time globally. We used a two-stages modelling approach, combining a statistical model based on environmental covariates and a mechanistic model which predicts soil C changes via landcover change, precipitation and temperature. The results successfully captures the effect of human pressure on natural environments and the subsequent loss of soil organic carbon with a prediction accuracy comparable with other digital soil mapping exercises. This work demonstrates the need to monitor and predict soil C change with time, and highlights the need of long term studies to unveil complex interactions in space-time.

Keywords: Soil security, Food security, Digital Soil Mapping, Google Earth Engine

Introduction, scope and main objectives

Soils fulfil a myriad of essential ecosystem functions, they are the foundation for producing food and fibre, store and filter water and also play a key role in the carbon cycle. The importance of the soil resource for human life and the need for its sustainable management have been a worldwide focus. A key driver for this recognition and increased public awareness was the declaration of 2015 as the International Year of Soils by the United Nations General Assembly (A/RES/68/232). "We need healthy soils to achieve our food security and nutrition goals, to fight climate change and to ensure overall sustainable development." (José Graziano da Silva, FAO Director-General).

Soil properties that can be used as indicators to detect substantial decline of the soil's condition have been discussed within the Soil Quality concept (Karlen *et al*., 2001) and within the wider Soil Security framework (McBratney *et al.*, 2014). Soil organic carbon fits well into the role of being a universal indicator for soil security as it is somehow known to the global population (Koch *et al*., 2013). It is therefore used here as a proxy to diagnose the condition of the soil resource.

Soil organic carbon is a key component of functional ecosystems and has been specifically linked to biological activity and agricultural productivity (Stockmann *et al*., 2013). Soil organic carbon has also become important as it can play a crucial role in climate change mitigation, through the offset of atmospheric CO_2.

Here, we quantitatively assessed the condition of our world soils, employing a unique spatial and temporal assessment of global soil organic carbon dynamics (including the distribution of SOC with depth). Such an assessment allows us to identify critical changes of the soil resource through time in light of land use change and changes in temperature and rainfall patterns, and will enable us to pinpoint regions of the world where the soil resource is at risk to fulfil its fundamental ecosystem functions.

Methodology

We performed a multiple-stage modelling, a combination of statistical and mechanistic inference. In brief, at the first stage we generated a baseline C map for the year 2001. To account for the C changes with time, on the second stage we performed a "landcover tracking" routine starting from our baseline, to establish where and when landcover changes occur, the nature of the changes, and how long the new landcovers persist.

Stage 1: SOC baseline generation
We based the first stage of our space-time modelling on the *scorpan* regression kriging approach (McBratney *et al*., 2003), where a soil attribute (i.e.: SOC) is a function of a series of soil forming factors which are represented by environmental covariates. In a digital soil mapping framework, these covariates are usually in the form of raster images. In this study we used the following set of covariates: a digital elevation model (Danielson and Gesch, 2011) and its derived slope, long-term mean annual temperature (MAT) and total annual precipitation (TAP) (Hijmans *et al.*, 2005), and land cover. To link the environmental covariates with the SOC content we used the CART algorithm (Breiman *et al*., 1984).

Stage 2: Landcover tracking
We used the MODIS Land Cover Type product (MCD12Q1), which provides annual global land cover information at a 500 m resolution, from the year 2001 until 2013 (which is constantly updated), using five global land cover classification systems. In this study we used the International Geosphere Biosphere Programme (IGBP) classification system (Belward, 1996).

We analysed each raster image since 2001 and kept track of all the landcover changes to establish if in any of the consecutive steps a positive or negative SOC concentration change would occur. The changes in SOC follow the dynamics described in the following Section.

Soil organic carbon dynamics

Magnitude of change: $\widetilde{m}$

When a landcover change occurs, it triggers a series of events leading to changes in the properties of the affected system, including SOC content. These changes usually happen over a period of time until the system reaches a new equilibrium. In this work we rationalise that these equilibrium states are related to the mean SOC content of each landcover. We also consider that landcover conditions change between climatic contexts, and to account for this difference we used the Köppen-Geiger climate classification scheme (Peel *et al.*, 2007) to group our observations.

Rate of change: $\tilde{r}$

The transition between the initial and the new system equilibrium state happens over a period of time, and together with the magnitude of the change, the rate for that change to occur is also dependant on temperature and water availability.

The temperature dependence (*vt*) is characterised by $e^{-E/k\,(T+273.15)}$, which is also known as the Arrhenius function (Arrhenius *et al.*, 1915), where *E* corresponds to an "activation energy", *T* is the MAT in Celsius, and *k* is the Boltzmann's constant (8.65×10^{-5} eV K^{-1}). By modifying the activation energy, this equation can be used to: a) describe SOC gains based on the temperature dependence of Rubisco carboxylation ($E \approx 0.32$eV), or b) describe SOC losses based on the temperature dependence of processes governed by respiration ($E \approx 0.65$eV).

The dependence on precipitation (*vp*) is described by a logistic function

$$vp = \frac{1}{1 + e^{0.003\left(pp - \frac{11401}{5}\right)}}$$

where *pp* is the total annual precipitation in mm. In this model, at low precipitation SOC flows are negligible (Ewing *et al.*, 2008), and after certain amount of water has been stored in the soil, its influence can be dismissed if we assume free-draining conditions. Similar logic has been used by Van Veen and Paul (2011) who used soil moisture deficit as a reduction factor to simulate SOC dynamics in grassland soils. The combination of both *vt* and *vp* yields to a normalised rate-modifying factor $\tilde{r}$,

$$\tilde{r} = \frac{r}{r_{max}}$$

$$r = vt * vp$$

where r_{max} represents the r value for the maximum temperature (32° C) and precipitation (11,401 mm) present on the covariates rasters (5.43 × 10−6 and 2.02 × 10−11 for gains and losses, respectively).

<u>Shape of change: $\tilde{s}$</u>

To account for SOC accumulation we generated a sequence of weights $\tilde{s}_{gain}$ using a logistic function, the length and shape of which depend on the value of the normalised rate-modifying factor $\tilde{r}$. A logistic function is a common form to describe growth. The Richard's equation (Richards, 1959), and Gompertz's function (Gompertz, 1825) are some examples. This type of function has also been applied to predict growth in forest ecosystems (Botkin, 1993; Pacala *et al.*, 1993), and crops (Yin *et al.*, 2003).

To simulate the SOC loss mechanism we used an exponential-decay function to generate a sequence of weights $\tilde{s}_{loss}$, which also depends on $\tilde{r}$. This type of curve has been widely used to describe SOC decomposition (Covington, 1981; Poeplau *et al.*, 2011).

By combining magnitude, rate and shape, it is possible to assess the differences in SOC for any given location after a landcover change.

Results and discussion

The numerical performance of our model is consistent with similar studies performed at national and global extent, with mean R^2 and RMSE values for the top soil around 31.59%, and 6.68% (SOC) respectively.

With our approach it is possible to predict SOC content for any given year between 2001 and 2013 (and further when new MODIS images become available), and by comparing multiple images it is possible to assess the change is SOC. Fig. 1 shows an example for Rondonia State in Brazil where anthropic pressure has led to expansion of agricultural land, and to deforestation. Similar results were obtained in many areas of the world (Fig. 2), highlighting the importance of landcover change as a driving force.

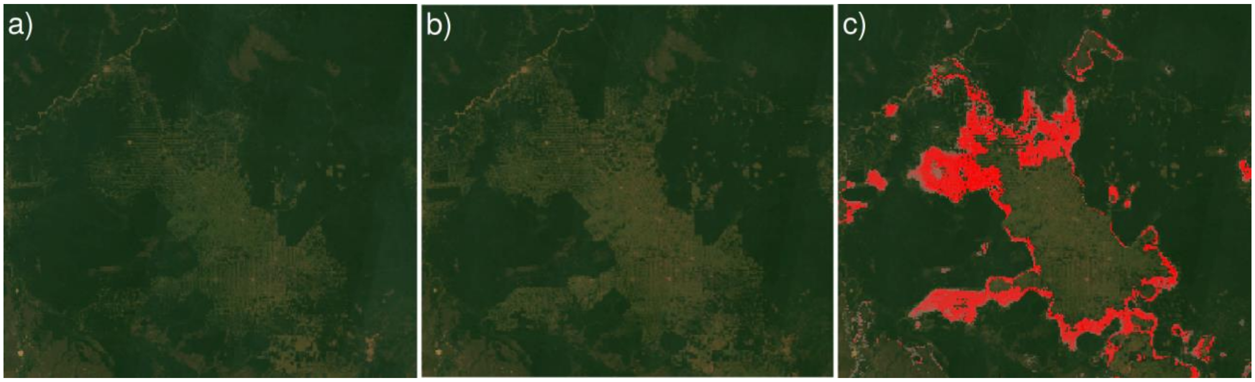

Fig. 1: Topsoil SOC loss in Rondonia State, Brazil. a) Satellite image for the year 2001; b) satellite image for year 2013; c) soil SOC for the year 2013 as compared to 2001, where red represent SOC loss.

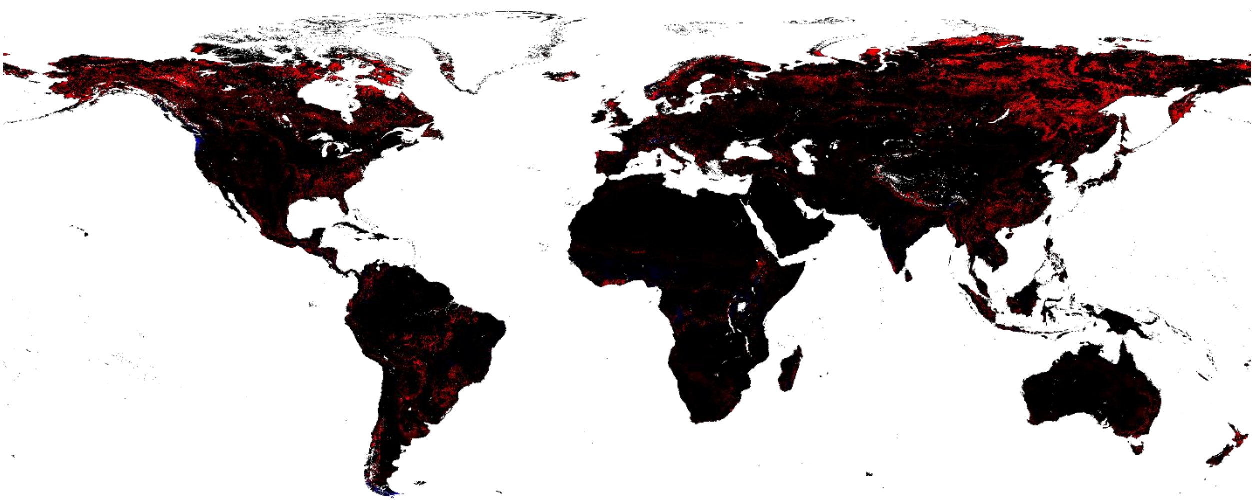

Fig. 2: Global topsoil SOC loss between 2001 and 2013.

Our approach clearly identify areas where SOC loss due to landcover change are expected. We did not find evidence of changes due to climate change in our data, and as a consequence, we ignored its effect, even if the mechanistic part of our model takes in account temperature and precipitation. We believe this is mainly because the low amount of soil chronosequence data in our dataset, and we stress the need to perform such studies in different bio-climatic regions.

Another important factor to consider is the uncertainty of the model. Our methodology assess the uncertainty levels of the modelling component, but has not considered the uncertainty of the MODIS imagery, which has a classification accuracy of around 75%. This inaccuracy leads to a general overestimation of the SOC loss, especially in boreal areas, according to our visual evaluation of the maps.

Conclusions

The proposed approach successfully captures the effect of human pressure on natural environments and the subsequent loss of soil organic carbon (SOC).

This work would not be possible without the collaboration of organisations who decided to share their soil data with us. Even if we assembled a relatively big dataset, most of the limitation of our model are defined by the absence of data, in particular in areas like peatlands, and other non-agricultural areas, and more specifically the lack of long term studies data to unveil the effect of persistent landcovers and climate change.

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