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Soil organic carbon stocks in Santa Cruz Island, Galapagos, under different climate change scenarios

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ABSTRACT

There is an increasing concern on how human activities could affect the ecosystems of the Galapagos Islands, a hot-spot for biodiversity recognized worldwide. Despite the high number of studies related to the ecological relationships between species in these islands, almost no research has been conducted on the description of their soils, a basic component of the ecosystems of Galapagos. In 1962, Belgian researchers from Ghent University organized a geo-pedological mission in order to collect detailed information on soil diversity on the Santa Cruz Island. Here we use this legacy data in a Digital Soil Mapping framework in order to quantify the spatial distribution of Soil Organic Carbon (SOC) stocks in this area. Our results indicate that the soils of Santa Cruz store about 706 Gg SOC in the upper 10 cm. SOC accumulation is mainly driven by climatic factors, which are highly influenced by both altitude and the direction of predominant winds. An increase in the amount of rainfall, as predicted by climate change scenarios, will result in an overall increase of the SOC stocks and likely modify the vegetation species composition within the different bioclimatic strata of the islands. A SOC monitoring program, based on spectroscopic analyses could be used to determine temporal variations in SOC stocks in a quick and cost-effective manner while minimizing human disturbances in this area.

1. Introduction

The Galapagos Islands are a pristine area that constitute an excellent location to study the impact of human activities on the environment (Huxley, 1966). Climate change was pinpointed as one of the major threats for the ecosystems in this area (d' Ozouville et al., 2009; Ebbesmeyer, 1991; Larrea, 2011). For the Eastern Pacific region, it was estimated that climate change will produce an intensification of El Niño Southern Oscillation (ENSO) events during the next decades, an increase in the sea surface temperature, rainfall rates and sea level and will decrease ocean pH and the intensity of ocean upwelling (Sachs and Ladd, 2010). The creation of an environmental monitoring system was suggested to detect the potential negative impacts of climate change in Galapagos (Larrea, 2011).

Both the recent Conference of the Parties COP21 and the Kyoto Protocol recognized the importance of Soil Organic Carbon (SOC) stocks as an effective way to evaluate and mitigate the impact of climate change (Lugato et al., 2015, 2014). SOC constitutes the largest pool of terrestrial organic carbon, acting as an important long-term sink for carbon released to the atmosphere by human activities (Falkowski, 2000; Lal, 2004). Monitoring changes in SOC stocks can be used as a tool to evaluate environmental threats associated with climate change. Digital Soil Mapping (DSM) includes a number of statistical techniques that make use of algorithms that relate the soil parameter of interest, measured on field observations, and a number of environmental auxiliary data measured at the same locations in order to predict the values of specific soil properties at unsampled locations (Hartemink et al., 2008; McBratney et al., 2003; Minasny and McBratney, 2016). The most popular DSM algorithms used to predict SOC stocks include multiple linear regression (MLR), ordinary kriging (OK), co-kriging, regression-kriging (RK) and geographically weighted regression (GWR) (Chen et al., 2000; Kumar et al., 2012; Kumar and Lal, 2011; Martin et al., 2014; Mishra et al., 2010; Phachomphon et al., 2010; Simbahan et al., 2006). These methods have advantages like their simplicity and straight-forward, intuitive interpretation (Grimm et al., 2008). Other methods like generalized linear models or machine learning approaches, which include among others artificial neural networks or tree models, have been also widely used for SOC prediction (Grimm et al., 2008; Henderson et al., 2005; Hengl et al., 2015; Kulmatiski et al., 2004; Minasny et al., 2006). McBratney et al. (2003) adapted the Jenny's equation of soil forming factors –climate, organisms, topography, parental material and time (Jenny, 1941) – to Digital Soil Mapping by including soil and space as new parameters to map soil properties. In oceanic temperate and tropical areas the SOC content is highly

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dependent on precipitation rates (Carvalhais et al., 2014; Fischer et al., 2014; Lal, 2004), indicating that climate is a main driver in the accumulation of SOC in these areas.

Due to state-mandated restrictions on soil collecting in the Galapagos, traditional methods for SOC sampling are generally not feasible (GNPD et al., 2015). In recent decades, soil spectroscopy presents an alternate method to minimize the environmental impacts of traditional soil surveys (Bellon-Maurel and McBratney, 2011; Linker, 2011). Spectroscopic analyses in the infrared range have many advantages like the possibility of making in situ measurements that provide the opportunity for monitoring soil properties in protected areas. Infrared spectroscopy is also more cost and time efficient than traditional chemical analyses. Several studies have proved the capacity of spectroscopy to predict SOC content making use of linear models such as MLR, partial least squares regression (PLS) and principal component regression (PCR) or more complicated and sophisticated approaches like boosted regression trees (BRT), artificial neural networks (ANN) or multiplicative adaptive regression (MARS) (Bellon-Maurel and McBratney, 2011; Linker, 2011; Reeves, 2010; Stenberg et al., 2010; Viscarra Rossel et al., 2006).

The objectives of this paper are: i) to determine the spatial distribution of SOC stocks, ii) to analyse the potential effects of climate change on such stocks for periods 2041–2060 and 2061–2080, and iii) to demonstrate the potential of infrared spectroscopic techniques to evaluate the SOC concentrations effectively compared to traditional methods.

2. Materials and methods

2.1. Soil sampling

Due to the difficulty of obtaining soil data in the Galapagos Islands at present, this study is based upon soil samples from the last geopedological expedition in 1962, which aimed to compile information about the islands' main soil types and properties (Stoops, 2014). The expedition described and sampled fifty-eight soil profiles across a transect from Academic Bay – southern coast of Santa Cruz Island – to an altitude of approximately 500 m. Between three and five horizons within each profile were properly sampled, stored and analysed in the laboratory (Stoops and De Paepe, 2013). Fig. 1a shows the distribution of the 36 topsoil samples recovered from this old expedition and used in this study. A description of each soil sample, as well as the topsoil depth to which they were collected, is included in the Supplementary information (Table S1). Samples were collected following the bioclimatic belts that exist in the Island. Table 1 summarizes the main characteristics of these vegetation zones.

2.2. Geochemical dataset and auxiliary rasters

The study uses data from both SOC concentrations and a number of environmental auxiliary data to model the present distribution and stocks of SOC over the entire archipelago and to predict the evolution of such stock over time for the periods 2041–2060 and 2061–2080.

2.2.1. SOC analyses

Total carbon content was measured by combustion using a LECO carbon analyser CHNS–932 (LECO Corp., St Joseph. MI) on the fine-earth fraction (Ø < 2 mm) of topsoil samples. The analysed soils do not contain any source of inorganic carbon, thus the obtained values correspond to Soil Organic Carbon (SOC).

2.2.2. Infrared spectroscopy

Soil samples were finely ground using a Retsch MM 301 Mixer Mill (model 01–462–0201). Fourier Transform Infrared Attenuated Total Reflection (FTIR-ATR) spectra were sampled at 4 cm^{-1} using an Agilent Cary 630 FTIR spectrometer (Agilent Technologies, USA) attached to a diamond crystal ATR device and a deuterated triglycine sulphate (DTGS) detector. Spectra were baseline corrected in order to avoid bias in the spectroscopic signal due to scattering, reflection, temperature, concentration or instrument anomalies (Griffiths and De Haseth, 2007).

2.2.3. Topographic parameters

A Digital Elevation Model (DEM) at 90 m grid resolution was downloaded from the CGIAR Consortium for Spatial Information (http://srtm.csi.cgiar.org/). The DEM was projected to the WGS84/UTM 15S (EPSG: 32715) coordinate system and used as a topographic template to calculate a map of wind effect. The map of wind effect (Böhner and Antonić, 2009) was calculated using the SAGA-Wind effect module within the Geographic Information System QGIS v.2.12. Fig. S1 shows both maps.

2.2.4. Rainfall data

Simulated precipitation raster maps, at 30 arc-second grid resolution, were obtained from the Global Climate Data repository for ecological modelling and GIS V1.4 (Hijmans et al., 2005) (http://www.worldclim.org/) for periods 1950–2000, 2041–2060 and 2061–2080. The maps were reprojected to the WGS84/UTM 15S (EPSG: 32,715) coordinate system. The precipitation maps representing future conditions correspond to the mean forecast obtained from 10 CMIP5 individual Global Climate Models (Table S2) and considering four different RCP scenarios. All these maps were downscaled to 90 m resolution by linear regression using the precipitation values at 30 arc-second resolution at sampling locations as the dependent variable and the respective values of altitude and wind effect at 90 m resolution as independent parameters (detailed methodology described in the next section).

2.3. Modelling procedures to obtain SOC distribution

2.3.1. Downscaling rainfall data

30 arc-second grid rainfall rasters (≈ 920 m) were downscaled to 90 m resolution data by relating rainfall data to elevation data and wind effect at the sampling locations by means of linear regression. The obtained models were then used to generalize the results of the different rainfall scenarios to the whole archipelago at higher spatial resolution.

2.3.2. Modelling SOC

Modelled precipitations for period 1950–2000 at sampling locations and square-root transformed SOC measurements were related by GWR, a method of spatially non-stationary linear regression. GWR is a statistical method that can be used to determine changing relationships in space between the dependent and independent variables (Brunsdon et al., 2010; Fotheringham et al., 2002). Model predictions at location i (Y_i) are obtained according to Eq. (1):

$$Y_i = \beta_0 (u_i, v_i) + \sum_k \beta_k (u_i, v_i) X_{ik} + \varepsilon_i \tag{1}$$

where (u_i, v_i) are the spatial coordinates at i, β_0 and β_k are the estimated regression coefficients, X_{ik} are the values of the independent variables at i and ε_i is the residual error. The regression coefficients (β) are determined by means of a weighting function, showed in Eq. (2):

$$\beta (u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i) Y \tag{2}$$

where X^T is the matrix of environmental variables, Y is the response variable and $W(u_i, v_i)$ are weighting factors used to estimate the influence of each observation on the predicted values within its neighbourhood (Fotheringham et al., 2002; Zhang et al., 2011). The GWR model was validated by using leave-one-out (LOO) cross validation, due to the limited number of observations in the dataset.

The values of SOC concentration (SOC%) predicted by GWR and soil bulk density was used to calculate SOC stocks. Soil bulk density (g