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Mapping soil organic carbon on a national scale: Towards an improved and updated map of Madagascar

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ABSTRACT

Assessment of soil organic carbon stocks (SOC_s) is highly relevant considering that SOC_s is the central driver in climate change mitigation and soil fertility. In Madagascar, a first attempt at mapping SOC_s on a national scale was undertaken in 2009 with previous soil data. Advanced research on soil carbon mapping on a global scale is required to enable better land use decisions. This study aims to (i) evaluate the drivers of soil organic carbon (SOC) storage in the first 30 cm soil layer on a national scale from spatially explicit explanatory environmental variables and a recent soil database and (ii) update the spatial distribution of SOC_s at this scale through digital mapping. A spatial model was established using randomForest, a decision tree algorithm and based on 10 pedoclimatic, topographic, and vegetation variables. The model was developed with 1993 available soil plot data (collected from 2010 to 2015) and their environmental information ("*VALSOL-Madagascar*" database). These data were divided into two sets: a first set ($n = 835$) used for model calibration and a second set ($n = 358$) for external validation. Results showed that mean annual temperature (MAT, °C), mean annual precipitation (MAP, mm), elevation (m) and Normalized Difference Vegetation Index (NDVI) were the most important predictors of SOC_s. The retained prediction model had a Root Mean Squared Error (RMSE) equal to 25.8 $MgC \cdot ha^{-1}$. The predicted SOC_s from fitted models ranged from 28 to 198 $MgC \cdot ha^{-1}$ with total SOC_s to 4137 TgC. Depending on soil type, Ferralsols (35 to 165 $MgC \cdot ha^{-1}$) and Andosols (48 to 198 $MgC \cdot ha^{-1}$) had relevant results related to the number of soil profiles ($n = 856$ and 171 respectively). Despite the need for in-depth analysis, the model and map produced in the present study has greatly improved our knowledge of the spatial distribution of SOC_s in Madagascar and reduced uncertainty compared to the former map. This map provides new perspectives in sustainable land management in Madagascar.

1. Introduction

Soils provide numerous ecosystem services but changes in land use and climate have affected their properties and functions (Millennium Ecosystem Assessment, 2005). Among these services, soil contains the largest pool of organic carbon in terrestrial ecosystems including forests, grasslands, agroecosystems and others (Batjes, 1996; Bolin et al., 2001; Matsuura et al., 2012; White et al., 2000).

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Soil organic carbon (SOC) maintains soil health and productivity of plant resources. It provides a primary source of nutrients for plants, helps particle aggregation and porosity promoting soil structure, increases water storage capacity and availability for plants, protects soil from erosion and provides a habitat for soil biota (Rossel et al., 2016). Carbon sequestration in soils can improve the quality and productivity of the soil to sustain food production and simultaneously mitigate emissions of greenhouse gases (GHG). Thus, soils have a huge potential for either sequestering or releasing carbon into the atmosphere (Kutsch et al., 2009).

Better understanding of ecosystem carbon balance is crucial for predicting carbon-climate feedback and guiding the implementation of mitigation policies (Fang et al., 2014; McKinley et al., 2011; Pan et al., 2011). Information about soil properties such as soil organic carbon stocks (SOC_s) could be very helpful in addressing climatic and environmental degradation issues and justifying SOC_s mapping.

Digital Soil Mapping techniques can potentially produce information about soil properties that are not currently available (Hempel et al., 2005; Legros, 2006). Moreover, they improve the consistency, accuracy, detail and speed at which soil survey information is produced. These techniques can be used both to update existing soil survey information and create information in unmapped areas (Lagacherie, 2007). In addition, a spatial soil information system created by a numerical model based on soil information and related environmental variables could account for spatial and temporal variations in soil properties (Lagacherie and McBratney, 2007).

In Madagascar, several attempts were made at mapping SOC_s on different scales. Locally, Razakamanarivo et al. (2011) mapped SOC_s for the first 30 cm depth in eucalyptus plantations in the central highlands of Madagascar by using multiple regression approaches. Grinand et al. (2009) produced a SOC_s map for the 30 cm top soil layer according to land uses and soil information at national scale. The authors used a georeferenced soil database named *VALSOL-Madagascar* (Beaudou and Le Martret, 2004) which gathered soil inventory data collected from 1946 to 1979. This first evaluation of organic carbon resource in Madagascar is however at coarse resolution (1 km) and display SOC_s levels that were observed more than thirty years ago. Considering the high rate of land use change especially related to deforestation (Harper et al., 2007) and nonsustainable agricultural practices (Vagen et al., 2006), digital SOC_s mapping is urgently needed in Madagascar, in order to reduce uncertainty at large scale, whilst improving the spatial resolution of the estimates. The map uncertainties are related to small sample size, uneven plot location, errors generated from laboratory analysis and land cover mapping from remote sensing. In 2015, the *VALSOL-Madagascar* database was updated and ongoing research is focusing on improving SOC_s maps on different scales by testing various digital spatial models (e.g.: randomForest, linear regression model, linear mixed effects models) combining large spatially-explicit environmental database with the most recent soil data.

The present study aimed to produce a national SOC_s map using the most recent soil information and relevant covariates explaining the SOC_s distribution. The main objectives of this paper were (i) to identify relevant factors controlling SOC_s (0–30 cm depth) (ii) to produce an improved national SOC_s map by using an updated soil database and digital soil mapping techniques.

2. Materials and methods

2.1. Study area

Madagascar is an island located in Eastern Africa in the Indian Ocean (between 11°57 and 25°29 South and 43°14 and 50°27 East) with a total surface area of 587,000 km^2. It has a unimodal tropical climate characterized by a wide climate gradients and vegetation changes (Styger et al., 2009). With an average of 7 dry season months, precipitation range from 500 to 3200 mm and temperature from 13 to 27 °C.

According to the soil map produced by Delenne and Pelletier (1980), Madagascar soil cover includes 11 soil types. Dominant soil types are Ferrallitic soils (Ferrasols, FAO, 2014) and Ferruginous soils (Ferric Luvisols, FAO, 2014) covering over 46% and 28% of national area respectively (Grinand et al., 2009) (Fig. 1).

2.2. Soil organic carbon stock database

In this study, 1193 soil plots dated from 2010 till 2015 were gathered and added in the national *VALSOL-Madagascar* database which is the only existing georeferenced soil database in Madagascar. These new data come from fourteen agronomical and environmental studies conducted throughout the country by LRI team and partners (Table 1). The *VALSOL-Madagascar* database was first established in 1980 and includes physical and chemical data on Malagasy soils gathered from old soil surveys carried out by the French Institute of Research for Development (IRD, previously called ORSTOM) between 1946 and 1979 (Leprun et al., 2010). *VALSOL-Madagascar* is currently being maintained through a close collaboration between the "Laboratoire des RadioIsotopes" (LRI) University of Antananarivo in Madagascar and the IRD. The updated soil database record soil information by vertical profile including geographical location, physical and chemical soil properties such as soil thickness, soil organic carbon content, bulk density, and soil texture (clay, silt and sand content). This available legacy soil data and information was harmonized for each plots in order to calculate SOC_s and to map spatial distribution of SOC_s in 0–30 cm depth similarly to other studies (Bernoux et al., 2002; Martin et al., 2011; Minasny et al., 2013; Nussbaum et al., 2014).

2.3. Calculation of soil organic carbon stocks

The SOC_s per soil profile in $MgC \cdot ha^{-1}$ were calculated using soil bulk density methods (Chapuis-Lardy et al., 2002; Razafimbelo et al., 2008; Razakamanarivo et al., 2011) and the carbon content was estimated using conventional Walkley and Black (1934) methods or combined with an alternative method using mid infrared spectroscopy (MIRS) analysis (Reeves, 2010). The calculation for each profile with *k* layers was performed as follows (Eq. (1)):

$$SOC_s = \sum_{i=1}^{k} [CCi \times BDi \times Di \times (1 - CFi)] \tag{1}$$

where SOC_s is the total amount of soil organic carbon per unit area ($MgC \cdot ha^{-1}$), CCi is the concentration of soil organic carbon in layer i ($gC \cdot kg^{-1}$), BDi is the bulk density ($g \cdot cm^{-3}$) of layer i, Di is the thickness of layer i (m), and CFi is the fraction of the volume of coarse fragments >2 mm in layer i (with $0 \leq CFi < 1$) (Batjes, 1996; Matsuura et al., 2012; Penman et al., 2003). For each soil profile, the SOC_s per unit area was calculated for a depth of 0–30 cm (3 layers: 0–10 cm, 10-20 cm and 20–30 cm).

2.4. Collection and harmonization of spatially-explicit covariates

In order to predict SOC_s, we considered potential, easy access and commonly used explanatory spatial variables (Table 2) (Grunwald, 2009; McBratney et al., 2003), that were either categorical dataset such as soil map and land-cover map, or continuous such as climate, topography, tree cover and satellite data.

Each available spatial data described below, were projected in the same spatial reference system (WGS84/UTM 38S) and resampled at 30 m × 30 m resolution which is the ground resolution considered appropriate for 1/100.000 scale mapping purpose (Legros, 2006). Explanatory variable values were extracted on each soil profile using GIS tools (QGIS software 2.6., 2014).

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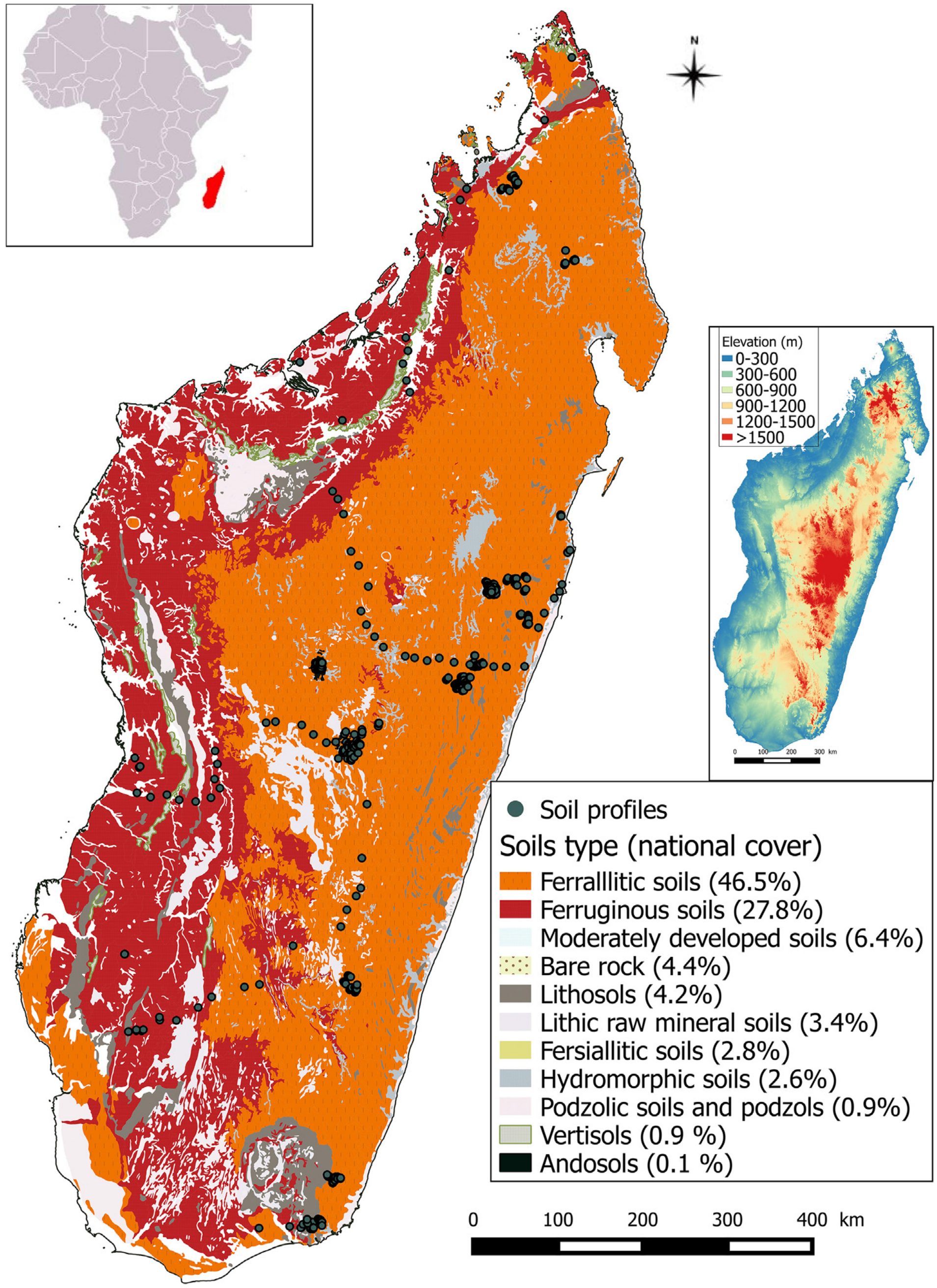

Fig. 1. Soil distribution in Madagascar (Delenne and Pelletier, 1980) with location of the 1193 soil profiles in *VALSOL-Madagascar* database.

Table 1
Descriptive statistics of SOC_s ($MgC \cdot ha^{-1}$) in *VALSOL-Madagascar* and Grinand et al. (2009) according to soil type by Delenne and Pelletier (1980) and corresponding to FAO (2014).

	Soil type	Soil type according to FAO (2014)	*VALSOL-Madagascar*					Grinand et al. (2009)				
			n	Mean	Min	Max	CV	n	Mean	Min	Max	CV
1	Ferrallitic soils	Ferralsols	856	88.3	16.8	232.8	0.39	89	61.3	5	163.2	0.62
2	Andosols	Andosols	171	117.5	22.7	225.7	0.45	4	90.8	62.1	120.3	0.36
3	Ferruginous soils	Ferric Luvisols	57	66.5	16.6	209.2	0.59	50	33.6	3.6	86.2	0.63
4	Hydromorphic soils	Fluvisols/histosols	51	87.6	18.8	177.9	0.34	40	75.9	9.9	161.1	0.49
5	Lithosols	Lithic Leptosols	44	82.7	13.7	157.6	0.48	4	33.6	21.4	52.5	0.40
6	Moderately developed soils	Cambisols	7	43.3	16.8	55.2	0.31	33	53.2	12.3	198.8	0.76
7	Podzolic soils and podzols	Podzols	3	52.6	18.8	78.9	0.58	1	66.6			
8	Vertisols	Vertisols	2	45.1	41.5	48.8	0.12	7	47.7	18.1	80.4	0.52
9	Fersiallitic soils	Alisols/nitisols	1	46.0	–	–	–	8	32.5	13.1	74.6	0.63
10	Bare rock	–	1	49.2	–	–	–					
11	Lithic raw mineral soils	Regosols/leptosols/arenosols	–	–	–	–		12	18.8	1.2	46.1	0.69
Total			1193	90.7	13.7	232.8	0.44	279	1.2	1.2	198.8	–

Table 2
Characteristics and statistics of SOC_s of predictor variables.

Type	Name (code name)	Unit	Type	Mean	Min.	Max.
Topography data	Elevation (Elevation)	m	Cont.	887	11	2121
	Slope (Slope)	%	Cont.	9.23	0.11	37.1
Climate data	Mean Annual Precipitation (MAP)	mm	Cont.	1586	554	3203
	Mean Annual Temperature (MAT)	°C	Cont.	20.2	13.2	27
Satellite derived data	Normalized Difference Vegetation Index (NDVI)		Cont.	0.56	−0.08	0.97
	Normalized Difference Water Index (NDWI)		Cont.	0.07	−0.37	0.43
	Normalized InfraRed Index (NIRI)		Cont.	−0.07	−0.43	−0.07
Vegetation data	Tree cover map (Tree_cover)	%	Cont.	60.13	0	100
	Land cover (Land_cover)		Disc	9 classes[a]		
Soil map	Soil type (Soil)		Disc.	11 classes[b]		

Cont.: continuous/quantitative data Disc.: categorical data.
[a] Cultivated areas, North Western dry forest, Wooded grassland/bushland mosaic, Grassland/wooded grassland mosaic, Western dry forest, Eastern humid forest, South Western dry spiny forest/thicket, degraded eastern humid forest, South western subhumid forest.
[b] Ferrallitic soils, Ferruginous soils, Moderaltely developed soils, Bare rock, Lithosols, Lithic raw mineral soils, Fersiallitic soils, Hydromorhic soils, Podzolic soils and podzols, Vertisols, Andosol.

2.4.1. National soil map

Delenne and Pelletier (1980) soil map is still the most national soil map and has been used in the present study (Fig. 1). It was developed using a modified classification of French Commission of Soil Science and Soil Mapping (CPCS, 1967) and adapted to the local context (Grinand et al., 2009). The classification system includes 11 soil types based on detailed descriptions of soil formation processes and profile characters (Duchaufour, 1998). The most extensive area according to soil type (74%) is occupied by Ferralsols (Ferrallitic soils) and Ferric Luvisols (Ferruginous soils), other cartographic units represent <10% of the area of the country. Table 1 presents SOC_s data distribution according to the previous soil map (Delenne and Pelletier, 1980) with the corresponding soil type following the Word Reference database for soil resources (FAO, 2014).

2.4.2. Land use and land cover

Vegetation data includes two sources of dataset. The first is a land-cover map (Land_cover) showing vegetation distribution derived from MODIS and Landsat 7 satellites at 30 m × 30 m of spatial resolution (Moat and Smith, 2007). The second is the Tree cover map (Tree_Cover) representing the percentage of tree cover within a 30 m pixel for the year 2000 derived from Landsat images (Hansen et al., 2013).

2.4.3. Climate

The climate dataset considered were: (i) mean annual precipitation (MAP, mm) and (ii) mean annual temperature (MAT, °C). They were derived from the WorldClim database which gather high resolution (1 km) climate dataset worldwide (Hijmans et al., 2005).

2.4.4. Topography

Topography dataset came from the digital elevation model provided by the French national geographic institute (IGN). Topographic data with a resolution of 90 m × 90 m is: Elevation (m) (Fig. 1), and Slope (%). Slope data was calculated on QGIS software (QGIS, 2014) using the elevation map (CNES, 2014).

2.4.5. Other soil and vegetation dataset

We used the 2014 Landsat cloud-free images composite (Hansen et al., 2013) to derive the soil and vegetation indexes: (i) Normalized Difference Vegetation Index (NDVI) map (Eq. (2)), (ii) Normalized InfraRed Index (NIRI) map (Eq. (3)) and (iii) Normalized Difference Water Index (NDWI) (Eq. (4)) by Gao (1996). NDVI was used as a potential indicator for growth and vigour of vegetation (Rouse et al., 1974). As NDVI saturates for vegetation with high greenness, NIRI and NDWI were also used. NIRI and NDWI are less prone to saturation (Mustafa et al., 2010) hence more appropriate for the humid tropical forest in the Eastern part of the island. They were considered also as a proxy of soil water content and ferrous oxide content which are strong indicator of soil types. Hereafter the formulas which were used to calculate these indices:

$$\mathrm{NDVI} = (\mathrm{NIR}-\mathrm{R})/(\mathrm{NIR}+\mathrm{R}) \tag{2}$$

$$\mathrm{NIRI} = (\mathrm{R}-\mathrm{NIR})/(\mathrm{SWIR}+\mathrm{NIR}) \tag{3}$$

$$\mathrm{NDWI} = (\mathrm{NIR}-\mathrm{SWIR})/(\mathrm{SWIR}+\mathrm{NIR}) \tag{4}$$

where NIR is the Near infrared band, R the Red band, SWIR the Shortwave Infrared band and G the Green band.

2.5. Soil organic carbon modelling

Spatially explicit SOC_s estimation was developed using the randomForest (RF, Breiman, 2001) algorithm. RF is a machine-learning algorithm that extends standard classification and regression tree (CART) methods by creating a collection of small classification trees (Wei et al., 2010). Unlike traditional CART analyses, the fit of each tree is assessed using randomly selected cases (1/3 of the data), which are withheld during its construction (out-of-bag or OOB sample).

The application of RF in the field of soil science is relatively recent but it is a potentially powerful approach for modelling in various soil-landscape regions and scales (Grimm et al., 2008; Grinand et al., 2017; Kim et al., 2012; Vagen et al., 2016). This model was also proved to provide accurate soil properties at continental scale (Hengl et al., 2015).

The whole 1193 SOC_s dataset were randomly divided into 2 sets: one for calibration (70% of the population n = 835) and one set for external validation (30% of the population n = 358). Once the model was created and validated, it was applied to the whole study area for the spatialisation.

RF modelling was performed using the randomForest package in R software (R.3.2.2).

2.6. Model evaluation

The quality of the model was evaluated by predicting the SOC_s values for the 30% sample data which is not used in the mapping exercise and by computing the R-squared (R^2, coefficient of determination) and the RMSE (Root Mean Squared Error ($\mathrm{MgC \cdot ha^{-1}}$)). The more R^2 is close to 1 and the lower RMSE is, the better and more robust the model is (Delmas et al., 2015; Hastie et al., 2009; Suuster et al., 2012). For this study, all of the variables were input for the randomForest model.

RMSE was calculated as follows (Eq. (5)).

$$\mathrm{RMSE} = \sqrt{\sum}\left[(\mathrm{d_i}-\mathrm{p_i})^2/\mathrm{n}\right] \tag{5}$$

where n was the number of observations in the external validation dataset, d_i was the observed SOC_s value, p_i was the predicted SOC_s value.

2.7. Relative importance of variables

RF provides a mean to assess the relative importance of predictors using two different metrics. Here, we used the Increased Mean Standard Error (%IncMSE). This metric is obtained by computing the difference between the OOB error of the calibrated tree model and after permuting each predictor variable (~random model), averaged and normalized over all the trees.

The most relevant variables in the model were further analysed using the *VSURF* package (Variable Selected Using randomForests). It is achieved by gradually adding variables to the model and picking the version of the model with the lowest Out Of Bag error (Breiman, 2001). The *VSURF* package returns two subsets of variables: the first is a subset of important variables including some redundancy which can be relevant for interpretation and the second is a smaller subset corresponding to a version of the model that tries to avoid redundancy and focuses more closely on the prediction objective (Genuer et al., 2014).

2.8. Verification of the accuracy of the map

The SOC_s map produced in the present was compared to the previous SOC_s map established by Grinand et al. (2009) and compared with reference dataset. We analysed the (i) SOC_s mean and range per soil type at country level, (ii) the overall SOC_s amount computing the SOC_s mean and total pixel area, and (iii) the SOC distribution and quality of each map. The latter was carried out at a local scale with the County of Didy, Ambatondrazaka District in the Eastern region of Madagascar. This county was selected for how representativeness of its SOC_s data was when compared to the average number for other counties. In order to test the accuracy of the newly produced map compared to the oldest available one, 1365 random points was created in this area by using QGIS, and the values of the prediction of each map was compared. Also, the limit of the produced map was verified by considering: the distribution of predicted pixel according to SOC_s values, the used resolution of spatial predictor variables, and the representativeness of sampling points in time and in space.

3. Results

3.1. Spatial model

The best fit model obtained showed a $R^2 = 0.59$ and a RMSE $=$ 25.8 MgC·ha^{-1} (Fig. 2). This model tends to underestimate SOC_s values higher than 150 MgC·ha^{-1} and overestimate SOC_s values below 50 MgC·ha^{-1} (Fig. 2).

According to the *VSURF* package all predictive variables were important for the model's construction, but the most relevant, with the highest relative importance index (%IncMSE) were: MAP, Elevation, MAT and NDVI. The %IncMSE of MAP-MAT-Elevation and NDVI were 741-712-693 and 327 respectively; which is higher than the %IncMSE values of the other factors such as NIRI-NDWI-Soil-Tree cover-Land cover and Slope (300-294-233-220-186 and 150 respectively) (Fig. 3).

3.2. Digital SOC_s maps and their variability

A map of SOC_s in the first 30 cm soil layer at national level was produced by using the best fit model (Fig. 4 and Table 3). SOC_s values from the produced map ranged from 28.3 to 197.6 MgC·ha^{-1}. For the whole country, the SOC_s total were 4137 ± 1214 TgC with a variation coefficient of 0.29. There were some gaps in regions with lithic raw mineral soils because of the inexistence of our SOC_s database and 3.4% of the area was not predicted.

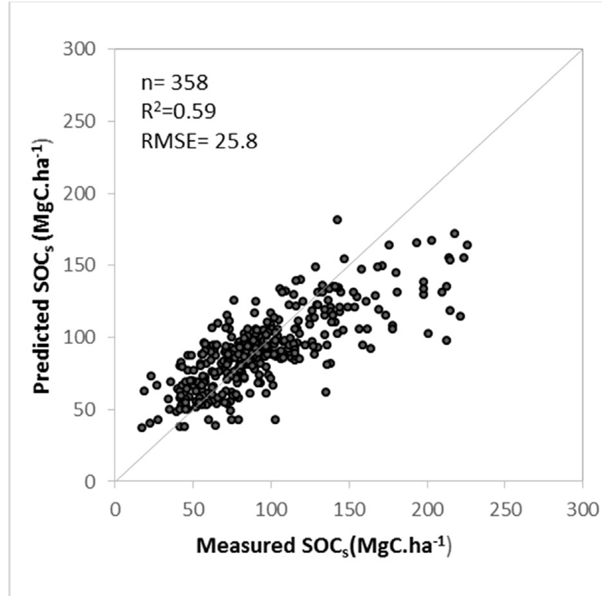

Fig. 2. External validation procedure results considering our best fit model.

In any case, according to soil type (Table 3), SOC_s values varied from 35.4 to 165.1 MgC·ha^{-1} in Ferralsol soils, 47.3 to 197.6 MgC·ha^{-1} in Andosols soils, 28.3 to 144.3 MgC·ha^{-1} in Ferric Luvisols (Ferruginous soil), 38.2 to 156.8 MgC·ha^{-1} in Fluvisols (Hydromophic soils) and 62.9 to 145.8 MgC·ha^{-1} in Lithosols (Lithic Leptosols). These soil types cover 81% of the area of Madagascar and were the most represented in our point sample dataset.

3.3. Comparison with existing SOC_s map

The total of SOC_s for Grinand et al. (2009) was 2583 ± 1565 TgC (CV $=$ 0.66), less than the results presented in this study. This difference can be explained by the lowest mean of SOC_s and the lowest number of soil profiles used for the mapping area occupied by the Ferralsol area (mean $=$ 61.3 MgC·ha^{-1}, n $=$ 89) and Ferric Luvisol area (mean $=$ 33.6 MgC·ha^{-1}, n $=$ 50) which are the dominant soils in Madagascar (Table 1).

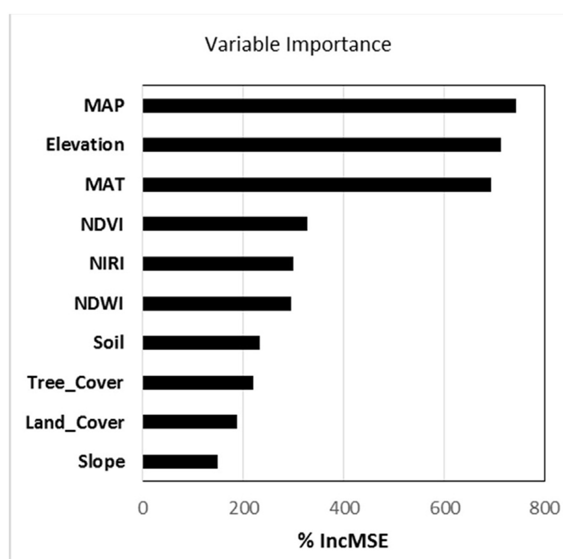

Fig. 3. Relative importance of variables.

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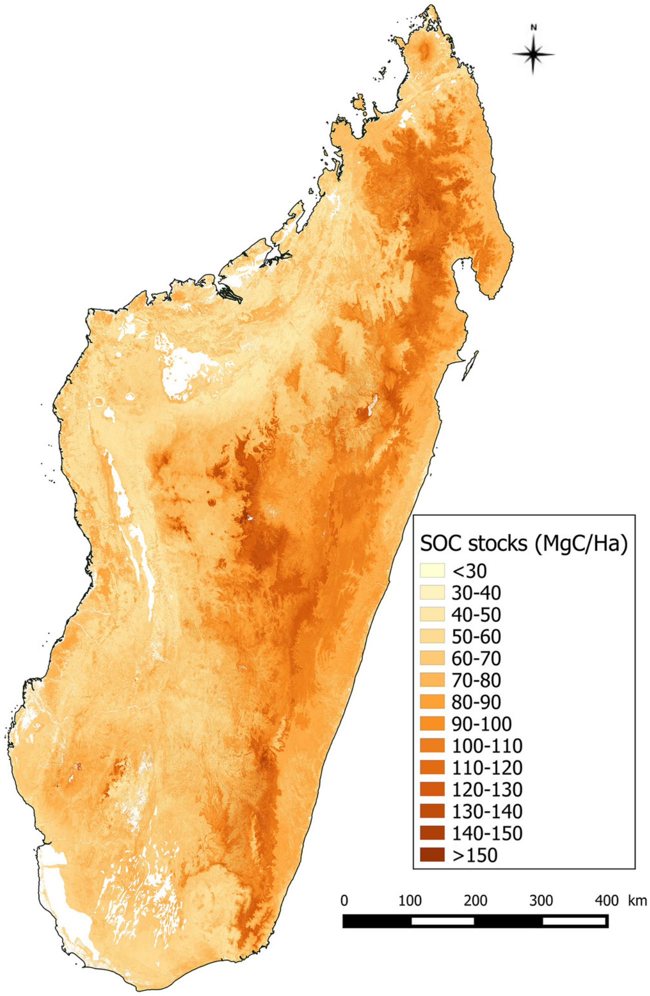

Fig. 4. SOC_s ($MgC \cdot ha^{-1}$) distribution map at national scale for the first 30 cm soil layer based on predicted SOC_s obtained by the use of spatial model generated by the randomForest algorithm.

In the county of Didy, Fig. 5 showed that the prediction of the two maps for the 1365 random points was different. The oldest map gave only eight values, compared to the new map. There was also a lot of non-predicted pixel compared to the actual maps. Grinand et al. (2009) used the average of SOC_s values for soil type and vegetation unit, and there is no change in SOC_s within the same map unit (Figs. 6 & 7). Our predictive model computes the value of each map pixel in accordance with the values of each variable in the regression trees.

4. Discussion

4.1. Relevant predictor variables of soil organic carbon stocks

Results of the prediction method showed that the spatial distribution of SOC_s is driven by a combination of elevation, climate and vegetation data (Fig. 3). The importance of these predictor variables differed according to the model. Precipitation, temperature, elevation and soil-vegetation index largely influenced the spatial distribution of SOC_s. These results were expected, as precipitation and temperature have a strong effect on Soil Organic Matter (SOM) decomposition (Grace et al., 2006).

Modelling of soil organic carbon by Were et al. (2016) showed that elevation was important for predicting SOC_s with other data such as silt content and satellite band. Indeed, in tropical soils, organic matter increases with precipitation, lower temperatures and elevation (Wang et al., 2013). Previous work reported that humidity and temperature decreased with altitude and these variables are the main factors behind the low rate of decomposition of SOM and thus the accumulation of SOC at higher elevation. Conversely, the speed of decomposition of organic matter increases with temperature, humidity and the oxygen content of soil (Wang et al., 2010). Also, organic material in the soil is essentially derived from residual plant and animal material due to the action of decomposition by microbes under the influence of temperature, moisture and ambient soil conditions (Yigini and Panagos, 2014).

A study by Sreenivas et al. (2014) found that NDVI and land cover were significant variables for predicting SOC_s on a model using climate data, NDVI, land-cover type, soil type and topography datasets ($R^2 = 0.86$). NDVI highlighted the vegetation percentage cover and the presence of vegetation in the area (Rouse et al., 1974). SOC_s result from the balance between inputs and outputs of carbon in the soil (Davidson and Janssens, 2006). Vegetation such as plant debris and roots from biomass are the "inputs", while the outputs are dominated by CO_2 flux of soil and methane (CH_4). Additionally, vegetation is strongly linked to the presence or absence of human activity in the area. Indeed, carbon mineralization of the soil depended on the changes in vegetation cover that are often modified by human activity (Martin et al., 2010). SOC_s is usually high in natural environments and decreases with land change (Lacoste et al., 2015).

4.2. Map prediction according to soil type

SOC_s of the new national digital map (mean = 71.1 $MgC \cdot ha^{-1}$) with variation coefficient of 29% is different compared to the values given by Grinand et al. (2009) which used 279 soil profiles (sampled before 1973). The range was from 1.2 to 198.8 $MgC \cdot ha^{-1}$ with estimated mean of 50.1 $MgC \cdot ha^{-1}$. This difference can be explained by the difference in SOC_s database which we used for modelling (Table 1). In this study, we used 835 plot data from 2010 to 2015 surveys. Moreover, the minimum

Table 3
Descriptive statistics of SOC_s ($MgC \cdot ha^{-1}$) for soil types (Delenne and Pelletier, 1980) according the newly produced national digital map.

	Soil type	Soil type according to FAO (2014)	n	Mean	Min	Max	CV
1	Ferrallitic soils	Ferralsols	592	81.0	35.4	165.1	0.24
2	Andosols	Andosols	126	116.4	47.3	197.6	0.25
3	Ferruginous soils	Ferric Luvisols	41	57.1	28.3	144.3	0.22
4	Hydromorphic soils	Fluvisols/histosols	31	81.3	38.2	156.8	0.22
5	Lithosols	Lithic Leptosols	34	62.9	34.6	145.8	0.27
6	Moderately developed soils	Cambisols	5	55.4	32.2	120.5	0.17
7	Podzolic soils and podzols	Podzols	2	61.0	34.4	128.3	0.11
8	Vertisols	Vertisols	2	54.8	32.7	92.1	0.18
9	Fersiallitic soils	Alisols/nitisols	1	60.4	36.3	123.9	0.12
10	Bare rock	–	1	75.4	35.4	154.5	0.28
11	Lithic raw mineral soils	Regosols/leptosols/arenosols					
TOTAL			835	71.1	28.3	197.6	0.29

n as number of SOC_s used on calibration model.

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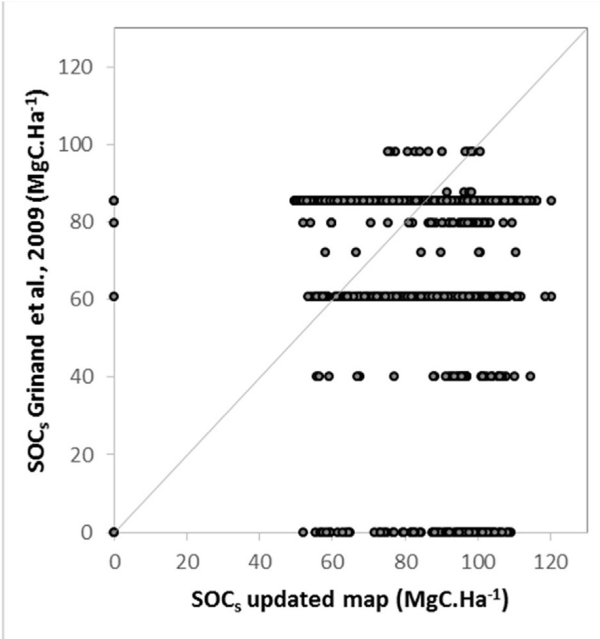

Fig. 5. Scatterplot of SOC$_s$ predictions proposed by Grinand et al. (2009) and by our model for random points (n = 1365) in the county of Didy.

value of Grinand et al. (2009) corresponds to lithic raw mineral soils (FAO, 2014: Regosols/leptosols/arenosols), in our case, the minimum value comes from the SOC$_s$ given on ferruginous soil (FAO, 2014: Ferric Luvisols) with a minimum of 28.3 MgC·ha^{-1} (Mean = 57.05 MgC·ha^{-1}). Razafimahatratra (2011) proved that lithosols, along with arenosol are both chemically exhausted soil types that are highly sensitive to erosion in perhumid tropics and with a lower SOC$_s$ content than that of Ferrallitic soils (FAO, 2014: Ferralsols; mean = 80.96 MgC·ha^{-1}, Table 3). The maximum value of our SOC$_s$ prediction comes from the values of andosols (max = 197.6 MgC·ha^{-1}; mean = 116.4 MgC·ha^{-1}), similarly to Grinand et al. (2009); these values correspond to moderately developed soils (FAO, 2014: Cambisols). Andosols have a tendency to bind organic matter and therefore often contain much more organic materials than other soils under similar conditions (FAO, 2014).

Considering determination according to soil type, the mean SOC$_s$ map predicted by our model was higher than those previously determined (Grinand et al., 2009), except for podzolic soils and podzols (FAO, 2014: Podzols) 66.6 MgC·ha^{-1} and 61 MgC·ha^{-1}. Therefore, our national model, did not predict SOC$_s$ values on lithic raw mineral soils because of lack of SOC$_s$ values on our updated database.

4.3. Limitations

The new national map produced with our method improved the spatial resolution, from 1 km for Grinand et al. (2009) (Fig. 7) to 30 m in the new digital map (Fig. 6). We showed also that accuracy was better, representing subtle SOC$_s$ change within the landscape. Although the spatial variables have a wide range of ground resolution, the downscaling in the finest resolution considers the gradients of the original resolutions such as climate data (Cavazzi et al., 2013) and topographic data (Grinand et al., 2017). For a model of SOC$_s$ with R^2 of 0.65, Vagen and Winowiecki (2013) showed that a SOC$_s$ map at 30 m resolution can assist with soil and landscape management. In addition, by using randomForest, Hengl et al. (2015) mentioned the better performance of an improved spatial resolution map.

According to the validation sample (Fig. 2), the main limit of the prediction was observed when predicting high SOC$_s$ values, thus affecting Ferralsols, Andosols, and hydromorphic soils (Fluvisols/histosols). However, according Fig. 8, pixels with highest values are scarce.

By considering the representativeness of the sampling points across the country, the range of collected data may affect the applicability of the model in different areas (Ryan et al., 2000). The prediction of SOC$_s$ should be improved by a good sampling design which follows a good representation of the spatial variables dataset (Ließ et al., 2016).

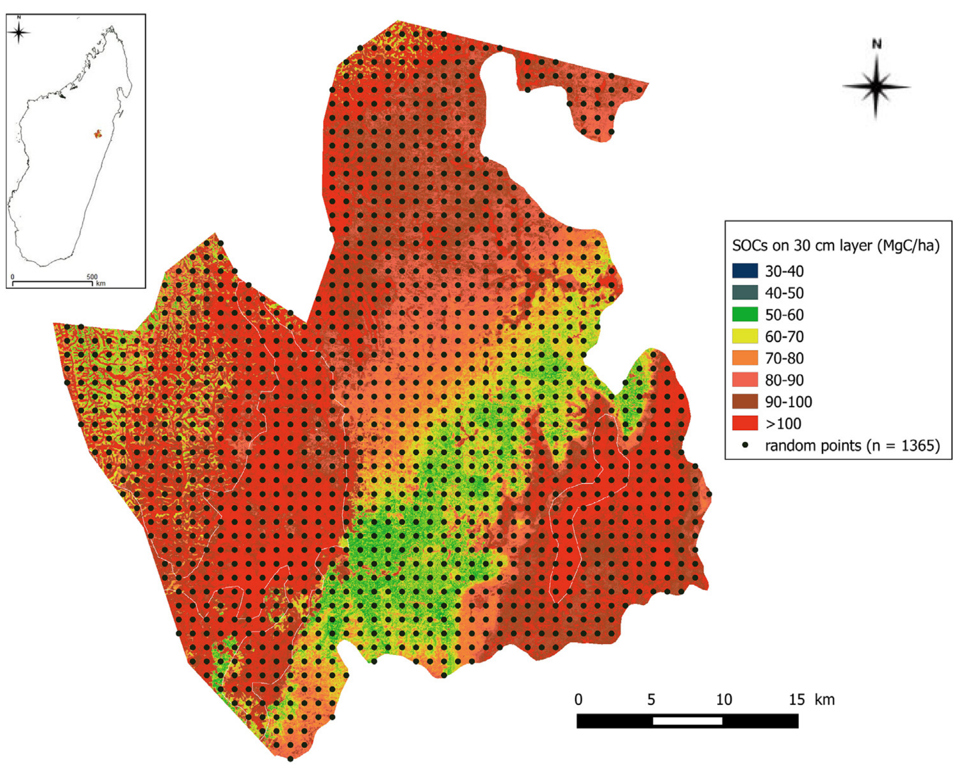

Fig. 6. SOC$_s$ map for the first 30 cm layer in the county of Didy according to the predictive model's national map.

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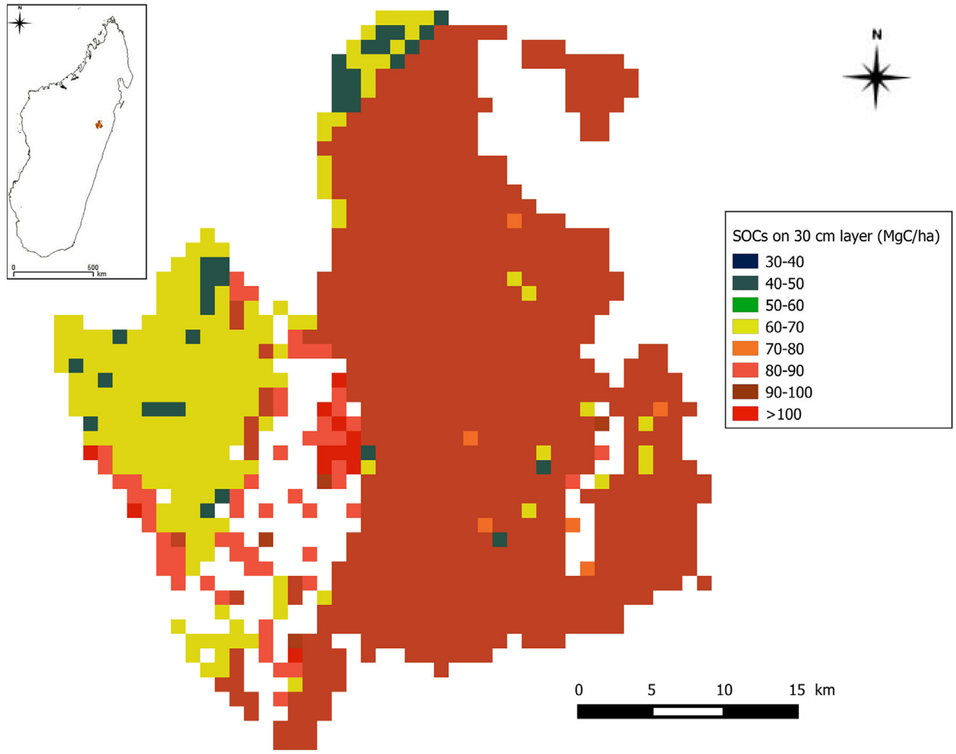

Fig. 7. SOC_s map for the first 30 cm layer in the county of Didy according to the national map by Grinand et al. (2009).

Another limitation could arise from difference in survey date. Most of the data used in our study were collected within the last five years and land use changes could have occurred between our study period and the older period considered by the Grinand et al. (2009) study. Also, the production of annual reference satellite cover of Madagascar at higher resolution, using for instance SENTINEL-2 images at 10 m resolution freely available from 2015, could be recommended to update the predictor variables related to satellite derived reflectance indexes.

Finally, the presence of unpredicted pixels challenged the research to work in other areas by collecting as much detail as possible about the physical and environmental characteristics, in particular soil type according the Word Reference Base of soil resources (FAO, 2014) and land use of sampling points.

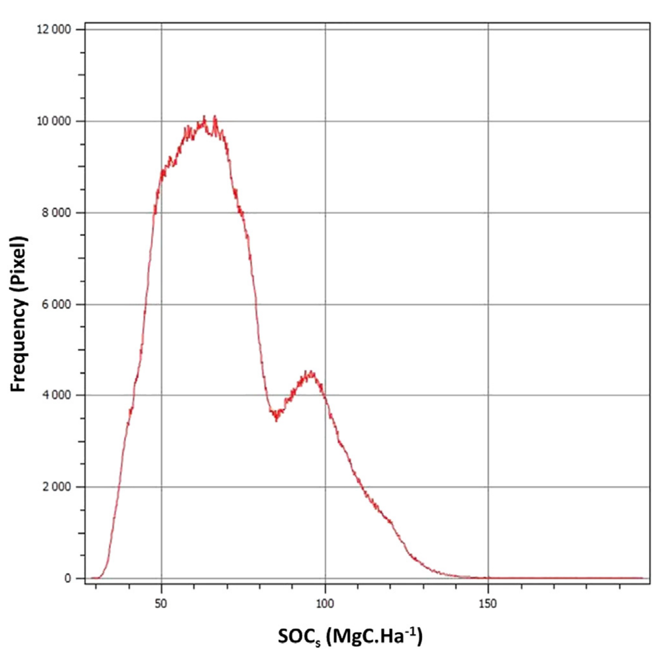

Fig. 8. Frequency of pixel according SOC_s map.

5. Conclusion

This study improved the scale and accuracy of the national map of SOC_s of Madagascar for the 30 cm surface soil layer in comparison with the one previously produced in 2009. The main innovation is the use of an updated database of recent soil surveys and newly available satellite data standardized at national scale. It could help to more precisely assess soil responses to environmental changes, including the assessment of C storage potential that is important for mitigating climate change, spatial distribution of SOC_s and the most relevant factors explaining SOC_s distribution. This map could be easily update as new soil data are been collected on the field and new spatial dataset are made available. Also, it can be served as basis for soil organic change detection at local and national extent. More research is needed in Madagascar to assess the land use and land cover change effect on soil organic carbon from landscape to national scale.

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(http://www.fsp-parrur.irenala.edu.mg/) (v) IFS: International Foundation for Science through a grant to RESEARCH GRANT AGREEMENT NO. D/5280-1 (http://www.ifs.se/) (vi) Holistic Program of Forest Conservation (PHCF) (http://phcf.actioncarbone.org/) (vii) PERR-FH: Ecoregional REDD + project, Eastern humid Forest funded by the Word Bank Institute (http://www.perr-fh-mada.net/) (viii) BIOVA project: Recycling Plant & Animal biomass in agricultural funded by European union and African Union (http://www.biova-project.org/). This work is also associated to the "Soil-carbon-Africa" network (http://reseau-carbone-sol-afrique.org/).

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.geodrs.2016.12.002.

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