#7659 SOIL ORGANIC CARBONE MAPPING IN NORTH OF TUNISIA: COMPARISON BETWEEN DIFFERENT INTERPOLATION METHODS

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ABSTRACT

Soil organic carbon (SOC) stock is an important carbon pool in terrestrial ecosystems. It plays an important role in agricultural productivity and is often used as a key indicator of soil quality whether for soil fertility or climate regulation. SOC stocks are difficult to estimate due to the large spatial variability. In this way, many different techniques have been conducted for predicting and mapping SOC content. However, although numerous techniques are in use, there is still debate on which is most appropriate for regional soil mapping. In this context, this paper discussed the application of geostatistical method to mapping SOC in North of Tunisia. 1097 samples of SOC were collected over the Northeast region from different sources. The selection of data was based on the rigor and credibility of the sources. The available data covered the period between 2000 and 2014. The sampling was carried out in the top soil (0-30 cm). Data were analyzed using geostatistical methods: simple kriging, ordinary kriging, universal kriging and inverse distance weighting (IDW) with the power 1, 2 and 4. These methods were compared using different performance criteria: normalized root mean square (RMSE), average standard error (ASE) and coefficient of determination (R^2). The best model for describing spatially variation of soil organic carbon was the ordinary kriging with the lowest error criteria and the highest coefficient of determination (R^2=0.6). The spatial structure of soil organic carbon is well described by the stable model. The nugget effect indicated that soil organic carbon was highly dependent on the study area (nugget/sill ratio=20%).

INTRODUCTION

Soil organic carbon is the main component of soil organic matter. As an indicator of soil health, SOC is important for its contributions to food production, it improves the structural stability of the soil by promoting the formation of aggregates which, in combination with porosity, provide sufficient aeration and water infiltration for plant growth (FAO, 2017). Soil organic carbon (SOC) is one of the soil properties that is not only key to sustainable soil fertility and productivity, but has become increasingly important as a major terrestrial carbon reservoir in the face of climate change (Wiesmeier et al. 2012). As COS is a spatially variable property, COS maps are of great interest for agricultural management as well as for environmental research related to terrestrial sequestration of atmospheric carbon (Liu et al. 2014). In fact, on a global scale, the soil C stock includes about 1500 Pg (1 Pg=1015 g) of soil organic carbon (SOC) (FAO, 2017). Small changes in the COS stock can influence atmospheric CO_2 concentrations and, in turn, have an impact on global climate (Lal, 2003). It is therefore very important to estimate this stock in order to explore areas of high and low COS stock potential for effective land-use management decisions. SOC distribution is affected by many factors, including climate, hydrology, soil type, land use, and others (McBratney et al, 2003, Cumble et al, 2013, Luo et al 2017), and its spatial variation is often wide and complex. SOC stocks are difficult to estimate due to the large spatial variability in a given soil (Cerri, 2007).

Therefore, quantitative evaluation of SOC levels is meaningful to facilitate regional planning and to provide decision makers with a reference tool. hence, SOC maps are of strong interest for agricultural management as well as in environmental research related to terrestrial carbon (Liu et al 2014). One of the most important challenges of digital soil mapping is the development of methods that allow the characterization of large areas with high resolution. Surface soils, which form the largest reservoir of the organic carbon, may be able to sequester atmospheric carbon and thus mitigate climate change. In that way, many different techniques have been conducted for predicting and mapping SOC content, such as the machine learning model (Ottoy and al, 2018; Wu and al., 2020), multiple linear regression (Ottoy and al, 2018), the random forest model (Nabiollah et al., 2019) and the geostatistical methods (Kumar et al,2012; Gol et al., 2017; Chabala et al,2017; Phachamphon, 2010). Although numerous techniques are in use, there is still debate on which is most appropriate for regional soil mapping. In this context, this paper discussed the application of the different geostatistical methods for the SOC mapping.

MATERIALS AND METHODS

Study Area

The study was conducted in the North of Tunisia. This region is characterized by three types of bioclimatic stage (humid, sub-humid and semi-arid). Northern regions where forests and fertile agricultural land. This region is divided into two regions; the very rainy regions where the rainfall is above 600mm. and the rainy regions where the average annual rainfall amounts between 400 and 600mm.

Soil Organic Carbon Data Base

A total of 1097points were gathered over the north region eleven governorate between 2000 and 2014, mainly by the Soil direction bulletins, analysis laboratories, research work (thesis, masters, etc.), scientific articles and annals of research institutes. The selection of data was based on the rigor and credibility of the sources. The data adequately reflect the distribution of the soil in this region. Soil samples were collected within soil profiles in the 0–30cm.

SOC Spatial Modeling

The spatial variability of SOC was studied using different geostatistical methods: ordinary kriging, simple kriging, universal kriging and IDW. It used to estimate a soil organic Carbone value at a region for which a variogram is known, using data in the neighborhood of the estimation location. The predicted SOC at an unsampled location using measured values. In fact, it used to describe how a soil organic carbon varies over the land surface. It demonstrates mathematically the means in which the variance of SOC varied as the distance and direction separating any two points. The process of modeling semivariogram function fits a semivariogram curve to SOC empirical data. An automated adjustment procedure was followed during the adjustment of the SOC semivariogram using the stable model for each geostatistical method. And we applied the power 1,2 and 4 for the IDW method.

To validate the spatial prediction of SOC, we used the leave-one-out cross validation. The indices used during this validation were determination coefficient (R^2), root mean square error (RMSE), average standard error (ASE), and standardized RMSE (RMSSE). Thus, for each of the sampled locations, there was a measured value SOC (x0) and a predicted value (SOC(xi)), The R^2, ASE and RMSE described by (Piccini et al., 2013).

RESULTS AND DISCUSSION

Variography and Interpolated Surfaces of SOC

Table 1 shows the variographic parameters. It was observed that the spatial autocorrelation was high for simple kriging and ordinary kriging with a nugget to sill ratio of 0.22 and 0.2 respectively and medium for universal kriging. The distance at which the sill is reached is 24 km for OK, 1km for SK and 6.2Km for UK it marks the limit of spatial dependence. This expresses that the places near to each another have a similar SOC while those more distant tend to have a more different soil on average this is explained by other intrinsic factors which can influence the SOC in particular, the type of soil, the land Use, agricultural practices etc.…This shows that semi variogram parameters obtained from fitting of experimental semi variogram values were reasonable to describe the spatial variation of SOC. Coupling the predicted and measured SOC in a cross validation indicated a positive relationship (R^2=0.6 for OK, 0.4 for both SK and UK). The three types of kriging showed very similar results but the ordinary kriging showed the best results R^2 higher and ASE and RMSE lower this is in accordance with the literature the OK is one of the geostatistical models that use a set of statistical tools to predict the value of a given soil property (in this case SOC) at a location that was not sampled (Johnston et al., 2001). OK is said to be an exact interpolator in the sense that interpolated values or their local average coincide with the values at the sampled locations (Chabala, 2017).

Table 1. Variogram characteristics and indices used for leave-out-one cross validation of kriging model for soil organic carbon prediction.

	Nugget	Range	Sill	NSR*	R^2	RMSE	ASE
OK	0.11	240	0.51	0.22	0.6	1.92	0.69
SK	0.08	10.5	0.4	0.2	0.49	1.93	3.02
UK	1.57	62	3.5	0.44	0.4	1.98	3.37

*NSR: Nugget to Sill ratio

For the IDW model results showed higher RMSE and lower R^2 compared to kriging this is can be explained by the better performance of geostatistical approach compared to deterministic one for mapping soil proprieties because the soil properties such as SOC do not depend on the distance only.

Table 2. Indices used for leave-out-one cross validation of Inverse distance weight (IDW) model for soil organic carbon prediction.

	Power	ME	RMSE	R^2
IDW	1	-0.07	2.93	0.4
	2	-0.06	2.99	0.34
	4	-0.05	2.10	0.3

Figure 1 illustrates the resulted maps of SOC distribution in North Tunisia based on different types of interpolation method. The maps show that the KS and KU underestimate the SOC stocks the SK considered the majority of the area with SOC stocks between 5 and 6Kg/m². Comparing the 6 resulted maps, the OK represents well the classes of the SOC. OK map show that the highest values of the stock are observed in the extreme North-West region in fersiallitic soils in forests with rainfall greater than 400 mm / year (humid bioclimatic stage) where recorded values are between 11.5 and 16.5 kg/m². High stocks are also observed in vertisols in forests (between 7.5 and 11.5 kg/m²) in subhumid climates in the Plains of Mateur, cultivated by cereal and fodder crop. Thus, values between 4 and 6 Kg/m² characterize the alluvial plains of the upper Madjerda valley formed of vertisols associated with poorly evolved soils of alluvial supply with annual rainfall greater than 400 mm.

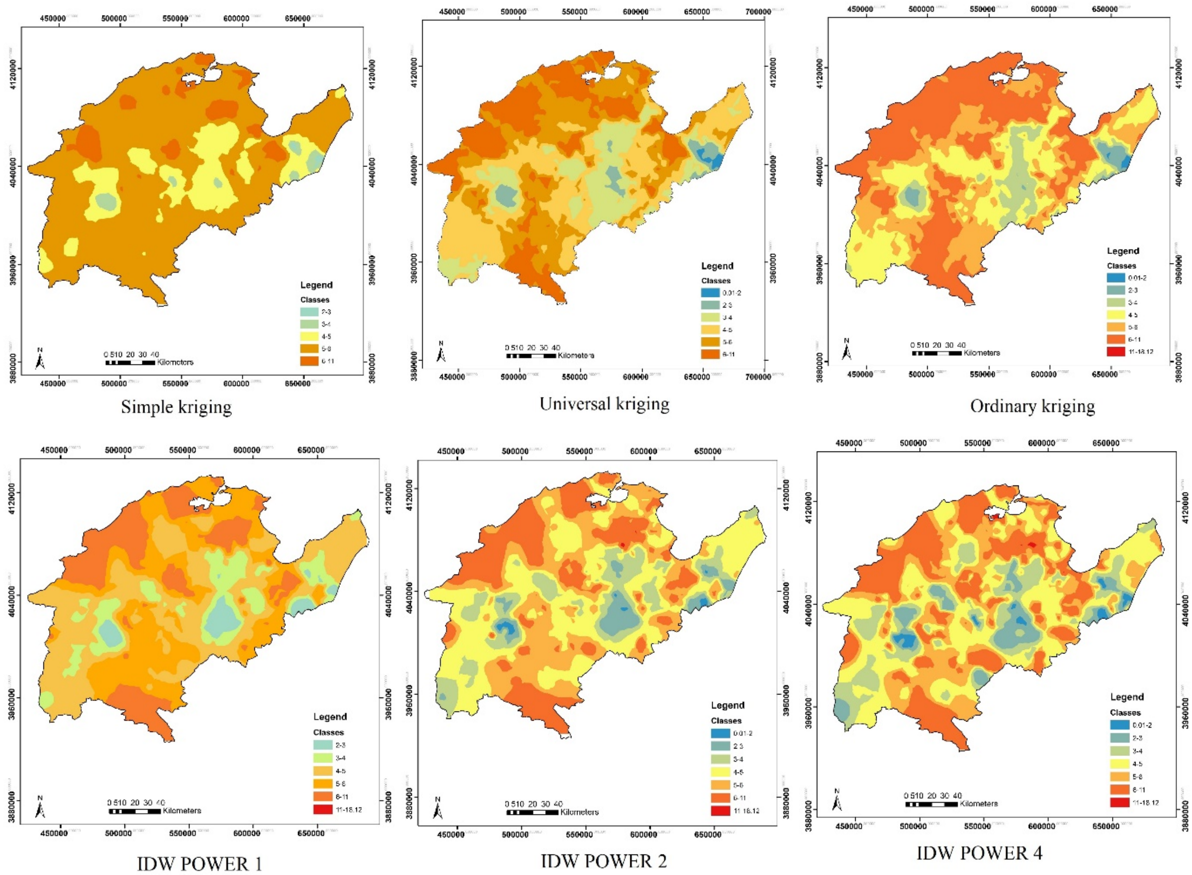

Figure 1. Maps of soil organic carbon (SOC) spatial distribution, generated based on kriging and IDW model in North Tunisian site.

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