

Modelling and Mapping of Soil Organic Matter in Doukkala Plain, Moroccan Semi-Arid Region

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ABSTRACT

The Doukkala plains one of the largest irrigated areas in Morocco with a very important agricultural potential. With the integration of new technologies in agriculture, the plain has been subjected to intensive agriculture which has negative impacts on soil quality especially the soil organic matter loss. Therefore, the objective of this study is to combine remote sensing and modelling for monitoring of organic matter content. The obtained results showed that all the examined models showed satisfactory results in the prediction of organic matter with a coefficient of determination R^2 ranging from 0.58 to 0.71 and the Root Mean Square Error (RMSE) varied 0.25 and 0.26%. Based on the findings, we can infer that this approach is both efficient and valid for modelling and mapping soil organic matter and may moreover be applied for other areas with same characteristics.

Keywords: Doukkala plain, modelling, mapping, soil organic matter.

INTRODUCTION

Currently, the large and steady increase in the world's population is causing increasing pressure on the world's soils. The role that soil can play in combating climate change by fixing carbon in the form of organic matter has recently received increasing attention (Francos et al., 2021). Soils are degraded due to erosion, compaction, sealing, salinization, decrease in organic matter, nutrient depletion, acidification, pollution and other phenomena caused by unsustainable land management practices, limiting their productivity (Brabant et al., 2010; Al Masmoudi et al., 2021). However, as a result of this degradation, the environment, particularly the groundwater, has also been affected in addition to the soil (Soudi et al., 1999; El Achheb et al., 2001) cited in (El Bourhrami et al., 2022). The capacity of a soil to

function in keeping environmental quality, biological production, flora and fauna health is described as soil quality (Coll et al., 2012), has become an increasingly useful method for assessing the impact of agricultural activity on soil sustainability (Amorim et al., 2020). It is critical to determine the content of soil organic matter (SOM) in order to achieve long-term agricultural development (Jiang et al., 2020). Thus, its effect on the fertility of the soil, its structure, its capacity of retention of moisture, plays an important role in their quality (Manlay et al., 2007; Lai et al., 2021).

It is an important component to monitor because a significant decrease in its content in mineral soils decreases aggregate stability and increases the soil's susceptibility to compaction and erosion. The evaluation of soil compaction is done indirectly with several methods, in this case by measuring bulk density, porosity,

organic matter and textural state (Al Masmoudi et al., 2018). In addition to improving water retention capacity, SOM is one of the main sources of nitrogen and minor elements useful to the plant (Guimarães et al., 2013). Soil properties are also modified by the semi-arid climate (Vasu et al., 2016; Bouasria et al., 2021). The Doukkala irrigated perimeter in the semi-arid region of Morocco, is one of the oldest and largest in the country in the Doukkala plain with a total surface area of 523 000 ha, and is experiencing an intensification of cultivation practices (Ibno Namr and Mrabet., 2004). In addition to conventional tillage and irrigation, the intensification of agricultural soil development in irrigated areas is accompanied by excessive mineral fertilization and poor management of organic matter and crop residues (Aghzar et al., 2002; El Baghdadi et al., 2012) cited in (Oumenskou et al., 2019), which causes a degradation of the soil and therefore a decrease in their quality (Badraoui et al., 2000; Naman et al., 2002; Naman et al., 2015).

Many techniques exist to quantify and characterize the physico-chemical properties of soil. Mapping the spatial variability of organic matter by interpolation remains a traditional prediction method (Zhai., 2019). In terms of resources and time, traditional field research, such as soil sampling missions and laboratory analysis, are thought to be expensive (Goidts and Van Wesemael., 2007) cited in (Laamrani et al., 2019) (Stenberg et al., 2010) as cited in (Stevens et al., 2013). Remote sensing is an efficient technique that can be considered an alternative to traditional soil analysis (Ben-Dor et al., 2009) cited in (Vereecken et al., 2016), and unable to provide detailed spatial distribution (Yu et al., 2021). For estimating a wide range of different soil parameters, spectral soil reflectance provides an attractive alternative to traditional laboratory-based soil physico-chemical analysis (Yu et al., 2015).

The SOM content of agricultural soils has been predicted and mapped using satellite images. This prediction is necessary in order to measuring the environmental quality and degree of degradation of the soil. A Multiple stepwise regression analysis (MSRA) model was applied, in order to predict the SOM content of soil in a remote sensing image because of its robustness and diverse applicability. This model established the relationship between the spectral reflectance of ground samples and their SOM content. When non-sampling points spectral reflectance data is

fed into it, the SOM content is the result of the regression equation's calculation (Ye et al., 2021).

Soil spectral curves contain very rich information, but also have redundant data affected by particle size, temperature, soil water, sampling manipulation, and the like. During the process of soil properties prediction, extracting relative information from the original spectral curve are very important (Zhu et al., 2018).

In the absence of modelling work in the study area, this study is important for the prediction of organic matter. Overall, the objective of this study is to combine remote sensing and modelling for monitoring of SOM content. As a result, the MSRA has been used for elaborating the model and a map of the SOM has been produced.

MATERIALS AND METHODS

Study area description

The Doukkala area is a vast plain of Atlantic Morocco inclined from SE to NW which is part of the Casablanca-Settat region and which extends over an area of about 6350 km². It is bounded to the northeast by Oum Er-Rbia basin, to the east by the Rehamena massif, to the south by the Gantour plateau and by the Atlantic Ocean to the west. The Doukkala irrigated area (Figure 1) is one of the largest irrigated areas in Morocco (Rahoui et al., 1999). It corresponds to a vast plain located south of the city of El Jadida on the Atlantic coast. It is irrigated from the Oum Er-Rbia basin that crosses the Doukkala region in central-western Morocco, known for its fertile plains. The water from the basin is diverted and distributed through a system of canals and pipes. The perimeter has a strategic importance for the national agricultural production, especially sugar beet crops (38%). The Regional Office of Agricultural Development in Doukkala (ORM-VAD) manages the Doukkala irrigation scheme, which is divided into two sub-areas: the lower section perimeter, which was impounded in 1958 with a total irrigated area of 61,000 ha, and the higher section perimeter, which was impounded in 1999 with a total irrigated area of 64,000 ha. From east to west, the latter has four main districts: Faregh, Sidi Bennour, Zemamra, and Gharbia. Each district is partitioned into a number of Irrigation Management Centers (CGRs) that are irrigated using three irrigation techniques (gravity, sprinkler and drip).

The study area (Figure 1) is located in the north-western part of the province of Sidi Bennour

in Morocco, between longitudes -8°51'0" W and latitudes 32°33'36" N. The study area is the Gharbia district, which is part of the Doukkala plain in the lower section perimeter. Its occupied agricultural surface is 13.100 ha. The 13,100 ha it covers are subdivided into 4 sectors: The South (3 500 ha), West 1 (2 400 ha) and West 2 (3 500 ha) sectors were impounded in 1982 and the North sector (3 700 ha) was impounded in 1984., the previous irrigation is sprinkler. Currently irrigated in drip. In this work we have chosen the Gharbia West 1 (2 400 ha) as study area. From a structural viewpoint, it belongs to mesetien area. Geographically, is located on the plains of the Doukkala, Morocco at 20 km from Oualidia, and 49 km north of Safi. The study area has a semi-arid climate, with mild temperate winters and generally hot and dry summers. The rainy season covers on average the period from October to May. The rains fall regularly in autumn and winter. Rainfall, which is estimated to average 317 mm per year, is decreasing. from the coast to the interior. Soils in this region are varied, from good quality and formed mainly from the silts. According to the French classification (CPCS, 1967), the plain's principal soil types are divided into six categories (Badraoui et al., 1993): isohumic soils, vertisols, calcimagnesian soils,

poorly evolved soils, soils with iron sesquioxides, and hydromorphic soil. These soils generally have an equitable surface texture that becomes clayey at depth with a dominant sandy fraction (fine sands in particular) (Rahoui et al., 1999). The soils that were analyzed were classed as vertisols. Agriculture (arboriculture, cereals, sugar beet, market gardening) is the most important economic activity in the area (Naman et al., 2001).

Methodology and data analysis

In July 2019, 52 soil samples were collected from 0–20 cm depth using a manually operated soil auger. Each sampling points coordinates were obtained by portable GPS (Garmin) and described using geographic information system software. SPSS 26 was used to process the field data statistically.

The Walkley-black method (1934) was used to analyze the content of SOM based on the principle of the oxidation of Soil Organic Carbon (SOC) by potassium dichromate ($K_2Cr_2O_7$) and concentrated sulfuric acid (H_2SO_4). The SOM content was calculated from organic carbon (OC) using the following Equation 1:

$$[SOM (\%) = OC (\%) \times 1.724] \quad (1)$$

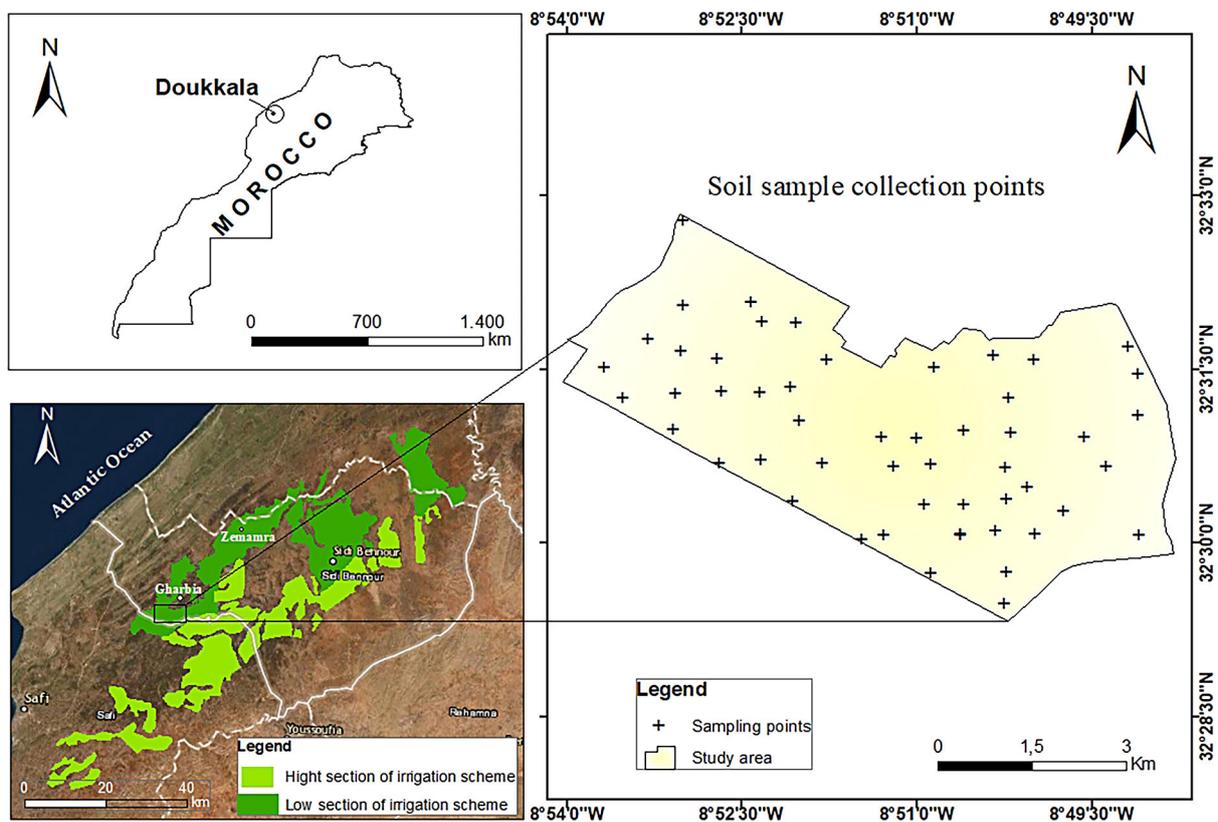


Figure 1. Location of the study area and sampling points

IDW Method

In this research, the Inverse Distance Weighted (IDW) method was examined for generate the spatial distribution map of SOM. IDW estimates are based on locations that are known to be nearby (Equation 2). Inverse distance from the interpolation point is used to provide weights to those points (Bhunia et al., 2018).

$$z(x_0) = \frac{\sum_{i=1}^n \frac{x_i}{h_{ij}^\beta}}{\sum_{i=1}^n \frac{1}{h_{ij}^\beta}} \quad (2)$$

where: $z(x_0)$ – the interpolated value;
 n – the total number of sample points;
 x_i – the measured value;
 h_{ij} – the separation distance between the interpolated value and the measured value;
 β – indicates the weighting power ($\beta = 2$).

Multiple stepwise regression analysis (MSRA) and validation

In this case, a statistical model based on MSRA was developed for model building based on Landsat OLI 8 image to estimate the SOM, using the following Equation (3):

$$Y = b_0 + b_1X_1 + b_2X_2 + \dots + b_kX_k \quad (3)$$

where: Y is the predicted variable with regression coefficients b_1 to k and Y -intercept b_0 when the values for the predictor variables are X_1 to k .

As a result, this work has been subdivided into six main steps: 1) Landsat OLI 8 image (path203/ row37) has been downloaded from the United States Geological Survey (USGS) website (<https://earthexplorer.usgs.gov/>), acquired on July 16, 2019 and the study area was extracted. 2) the image has been radiometrically calibrated and atmospherically corrected, an image pansharpener processing was applied to produce a PAN image with 15m of resolution from 30m image resolution. 3) the integration of the parameters including the visible bands (bands 2–4), the Near Infrared band (NIR) (band 5), the Shortwave Infrared (SWIR) 1 (band 6) and the Shortwave Infrared (SWIR) 2 (band 7). 4) integration of laboratory measurements. 5) statistical analysis and modeling and 6) selection of most appropriate model and computation of the spatial mapping of soil organic matter. The coefficient of determination

(R^2), the root-mean-square error (RMSE) (Equation 4) and the p-value were used to validate the selected models. An outline of the methodology employed is shown in Figure 2.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y(i) - \hat{y}(i))^2}{N}} \quad (4)$$

where: y_i and \hat{y}_i – respectively the observed and estimated values of the SOM content;
 N – the total number of observations ($N=52$).

RESULTS AND DISCUSSIONS

Descriptive statistics

The description of the data set includes examination of the mean, standard deviation, coefficient of variation, skewness, kurtosis and extreme minimum and maximum values of soil organic matter was obtained using SPSS Software (Table 1). The skewness and kurtosis coefficients are often used to describe the shape and flatness of data distribution respectively.

Test the normality for SOM

The Q-Q diagram (or quantile-quantile diagram) and normal histogram, are graphical tools that helps us assess whether our data set plausibly comes from a theoretical distribution such as a normal or exponential distribution. They were produced to identify probabilities and obvious outliers (extreme values). SOM followed a straight diagonal line, with the exception of a few samples that deviated slightly from the majority at the left end, which should visually indicate that our data are approximately normally distributed, in terms of normal histograms and Q-Q plots (Figures 3, 4).

Soil organic matter content analysis is usually used to determine the level of soil organic matter richness. The following percentages are usually considered:

Several research studies have been carried out in this context, showing the importance of soil organic matter in assessing soil quality. The results showed that the soils have less than 2% organic matter. The values of SOM vary from 0.93% to 1.62% with an average of 1.38% (Table 1). According to the interpretation standards (DIAEA / DRHA / SEEN, 2008), 79% of the analyzed soils were classified as poor and 21% as moderately poor in SOM (Table 2).

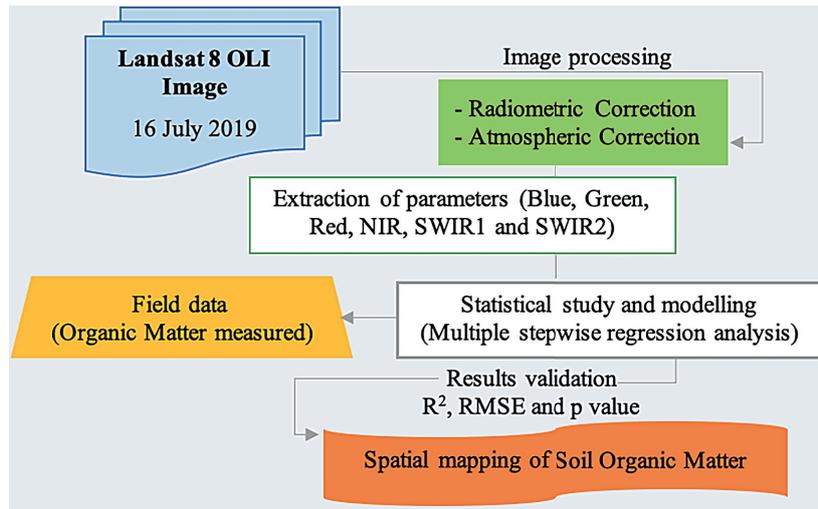


Figure 2. Flowchart of the methodology employed

Table 1. Descriptive statistics of SOM (N=52)

Indicator	Minimum	Maximum	Mean	SD	CV	Skewness	Kurtosis
SOM %	0.93	1.62	1.38	0.17	12.3	-0.9	0.4

Note: SOM – soil organic matter (%), SD – standard deviation, CV – coefficient of variation

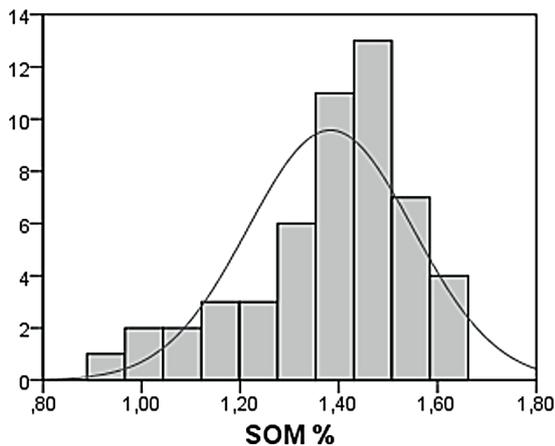


Figure 3. Simple bar of soil organic matter

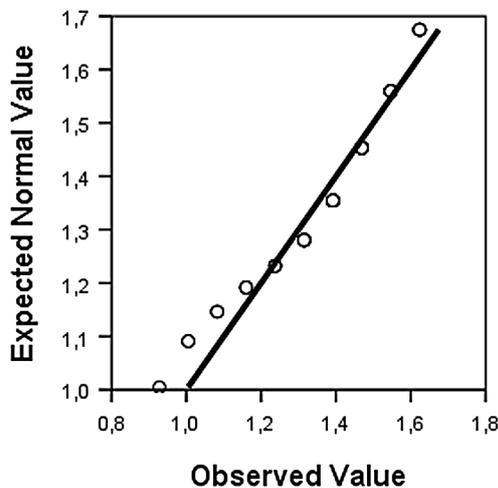


Figure 4. SOM Q-Q plot (N=52)

Table 2. Distribution of Soil organic matter classes according to DIAEA /DRHA /SEEN standards (2008)

Soil class	SOM (%)	Samples (%)
Very poor	< 0.7	0
Poor	0.7–1.5	79
Moderately poor	1.5–3	21
Rich	3–6	0
Very rich	> 6	0

The spatial distribution of SOM

The following Figure 5 shows the spatial distribution map of SOM using the IDW method interpolation. The map shows that the moderate SOM values are located in the southeastern and middle parts, but the low values are observed in the western and northeastern parts.

This low concentration indicates a degradation of soil that contributes to a decrease in their quality and this can be explained by the influence of the semi-arid climate (Badraoui, 2006; Naman et al., 2015; Bouasria et al., 2021). This degradation is caused by a very strong intensification of the agricultural lands, due to the installation of an important hydraulic infrastructure, for the irrigation of the soils. The annual loss of organic matter related to the clay fraction has been estimated at 30 kg per hectare per year (Naman et al., 2002). Badraoui et al. (2000) studied the evolution of

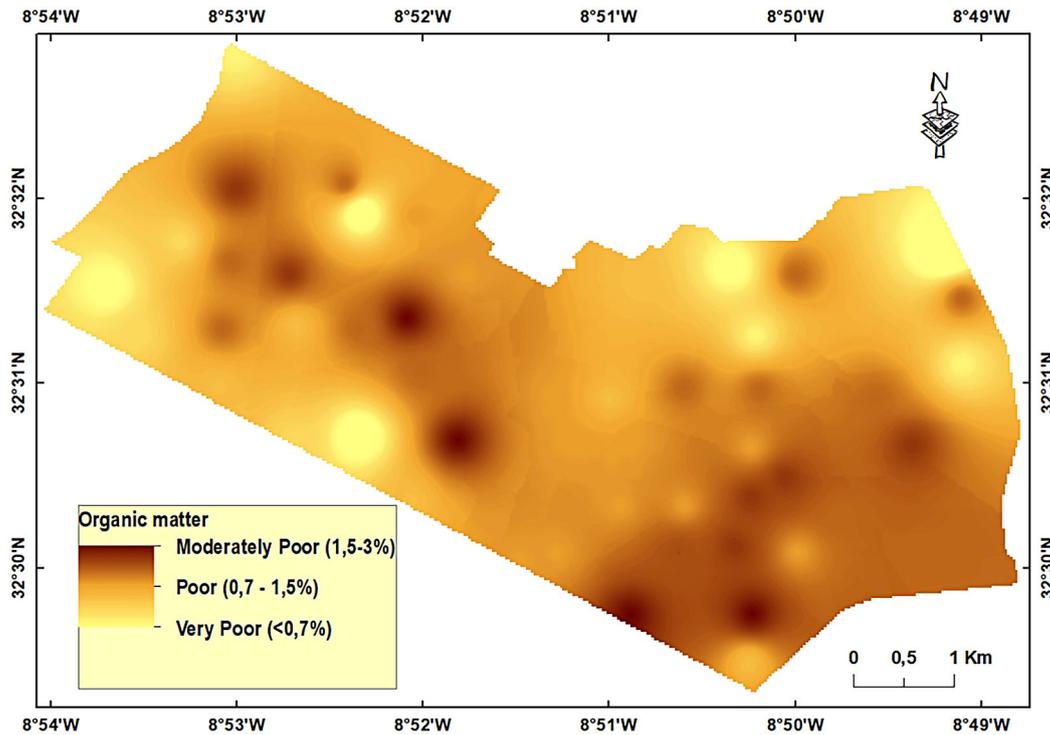


Figure 5. Spatial distribution maps of SOM derived by IDW

soil quality between 1987 and 1997 in the irrigated perimeters of Doukkala, they were found to have significant losses in soil SOM (30% for Vertisols). This decrease in SOM could be attributed to agricultural practices, mostly intensive tillage and bad residue management (Rahoui et al., 2000; Naman et al., 2001; Bouasria et al., 2020). This loss of organic matter can be corrected by organic amendment (composts, crop residues, green waste).

Model validation and evaluation

Table 3 shows the SOM prediction models and their characteristics. In order to be integrated into the models, the bands were selected based on their positive correlation with

the SOM. Then, the MSRA was chosen for the generation of the different models. As a result, several models were developed, and only those with a high coefficient of determination and a very low RMSE were considered. The results showed a moderate coefficient of determination for model 4 with a value of 0.57, while for the other models this index is acceptable with values of 0.60, 0.67 and 0.70 respectively for the models 1, 2 and 3. While RMSE values are generally around 0.25 for the two models 1 and 3, for the other two models 2 and 4 the RMSE is around 0.26 (Figure 6 and Table 3).

The laboratory measured and estimated value of the SOM were reported with their equations to validate the efficiency of the suggested models (Figure 6).

Table 3. Statistical parameters of the best performance models

Model	Variables	R ²	RMSE (%)	P value	Model equation
1	BLUE, GREEN, RED, NIR, SWIR1, SWIR2	0.605	0.25	0.004	SOM = 2.5 - (290.97 * BLUE) + (345.21 * GREEN) - (49.73 * RED) - (57.46 * NIR) + (58.4 * SWIR1) - (56.92 * SWIR2)
2	GREEN, RED, NIR, SWIR1, SWIR2	0.673	0.26	0.008	SOM = 1.55 + (46.9 * GREEN) + (25.05 * RED) - (37.99 * NIR) + (28.72 * SWIR1) - (46.6 * SWIR2)
3	RED, NIR, SWIR1, SWIR2	0.705	0.25	0.004	SOM = 1.74 + (54.27 * RED) - (33.8 * NIR) + (20.45 * SWIR1) - (40.6 * SWIR2)
4	BLUE, NIR, SWIR1, SWIR2	0.579	0.26	0.002	SOM = 0.92 + (91 * BLUE) - (34.14 * NIR) + (43.46 * SWIR1) - (53.65 * SWIR2)

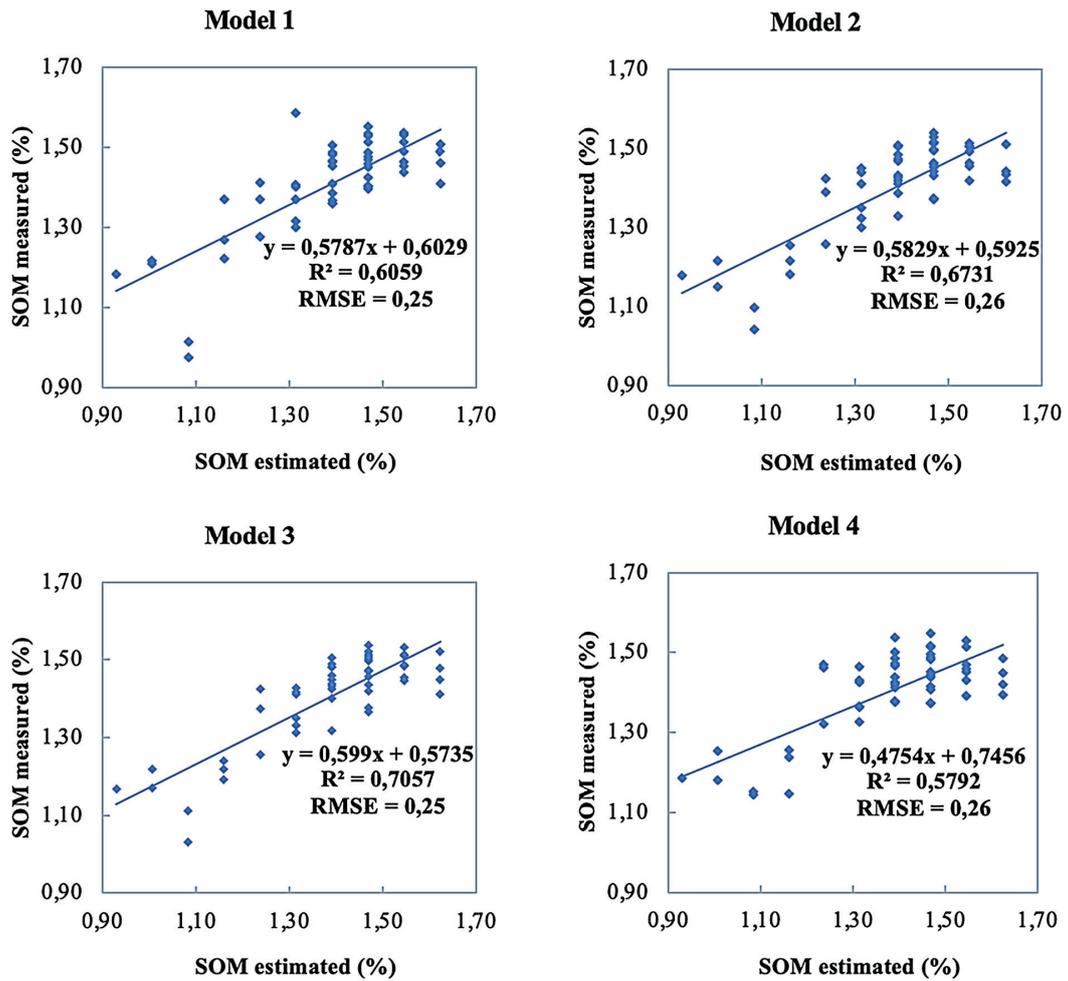


Figure 6. SOM measured versus SOM estimated through the models

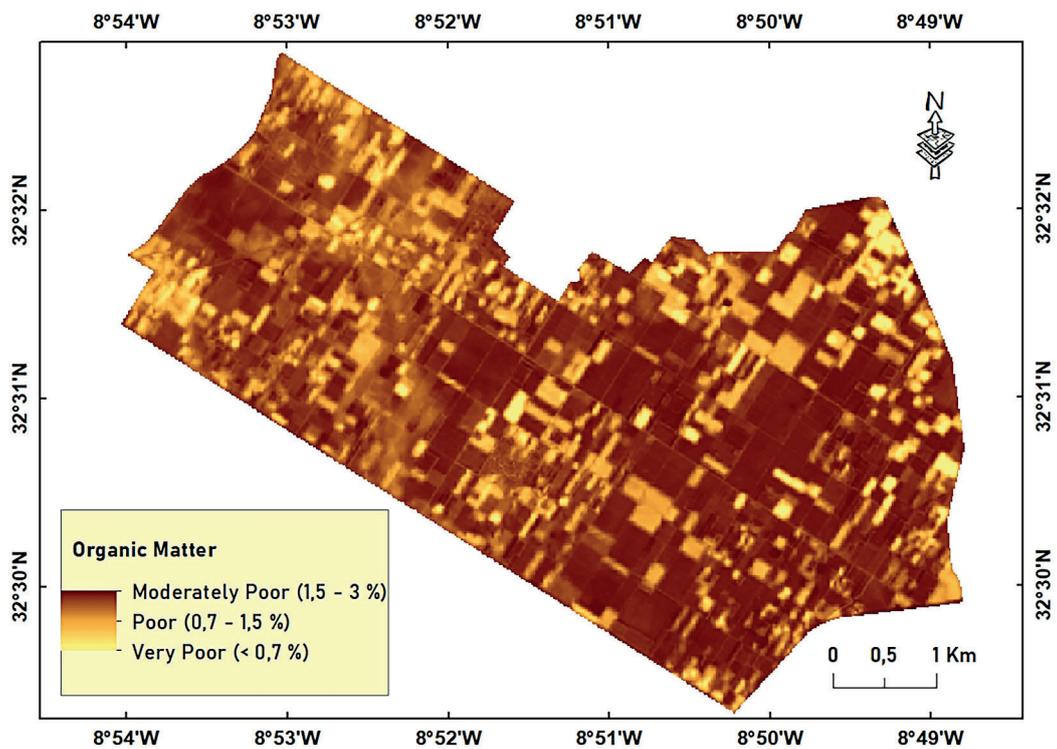


Figure 7. SOM-based model considered (Model 3)

The use of satellites in agriculture allows the management and monitoring of agricultural practices at different scales: national, regional, local and parcel, in order to establish a diagnosis of the parcels: inter-parcel comparison, to guide the decisions of production management and optimization of the farm; intra-parcel analysis to optimize the use of inputs to crops (fertilizer, water, etc.). Soil quality is represented by different physical, chemical and biological soil parameters, of which organic matter plays a major role. The estimation of these parameters remains costly and time-consuming and difficult in terms of sampling and their laboratory analysis. The IDW map (Figure 5) shows an irregular spatial distribution in the area. This interpolation method gave a general idea of the SOM content in the study area and not in terms of individual plots, but the mapping of SOM (Figure 7) using the predicted model allowed us to identify plots with low SOM content.

However, the predicting of SOM by the MSRA has shown significant results ($R^2 = 0.71$ and $RMSE = 0.25$). It has been used as an alternative to laboratory analysis using remote sensing data combined with laboratory measurements to validate the model predicted by this approach. Modelling, therefore, can help make decisions about the correction of SOM content for deficient plots, and thus contribute to improve the fertility of the plots and allow the sustainability of the soil system and guarantee better crop yields.

CONCLUSIONS

Organic matter is a major indicator of soil fertility and their degradation. This study aims to model and map SOM by integrating remote sensing data and laboratory measurements. The results obtained from the organic matter analyzed in the laboratory show that 79% of the analyzed soils are poor (<2%) and 21% are moderately poor in SOM.

The combination of Landsat-8 OLI data and the data measured in the laboratory allowed to generate a suitable model for the SOM mapping. 4 models were tested for the SOM modeling, they showed a good correlation between the measured and estimated values (R^2 between 0.58 and 0.71 and the RMSE between 0.25 and 0.26%). The model selected to generate the SOM distribution map (R^2 of 0.71, RMSE 0.25% and a p-value of 0.004), it groups the RED, NIR, SWIR

1 and SWIR 2 bands. This modelling provides information that can support SOM management decisions. This study is the first attempt to test the ability of the Landsat 8 OLI satellite in combination with remote sensing to predict SOM in our study area.

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