Spatio-Temporal Modelling of Relationship Between Organic Carbon Content and Land Use Using Deep Learning Approach and Several Co-Variables: Application to the Soils of the Beni Mellal in Morocco

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Abstract: In recent decades, population growth has led to rapid urbanisation associated with a land degradation process that threatens soil organic carbon stocks (SOCS). This paper aims to model the interrelationships between SOCS and land use/land cover (LULC). The approach was based on the use of environmental covariates derived from Landsat-5 TM/8 OLI images, forty soil samples, Kriging spatial interpolation method and a Multi-layer Perceptron (MLP) model for the geo-spatialisation of SOCS. The analysis shows a high positive autocorrelations (R^2>0.75) between vegetation indices and SOCS, particularly higher for SOCS derived from spatial modelling with MLP. On the other hand, the relationship between LULC and SOCS from the three approaches is very variable depending on the dynamics of LULC. The autocorrelations between SOCS and LULC units are very weak in 1985 and 2000 but significant for the year 2018. This suggests that the land use dynamics in the area are favourable to SOCS. In general, the results show that SOCS increased in the tree crop, unused land and forest areas but decreased in the cropland. The SOCS varied in the following order: forest cover>unused land>cropland>urban area>tree crops. This indicates that LULC, topography and vegetation types had an impact on SOCS distribution characteristics.

1 INTRODUCTION

As the living foundation of agricultural and forestry production, soil is a finite and non-renewable resource on a human lifetime scale. It is subject to several increasing pressures that lead to tensions between land uses (Lal et al. 2007). Changes in agricultural production methods, the reversal of grasslands, the loss of arable or wooded land to urbanisation, the increase in biomass extraction, etc., are all developments which, if not properly considered, could affect the quality of soils, and dissipate the carbon stocks they contain. Soil is a complex system that plays a central role in agricultural and forest ecosystems by regulating various natural cycles such as those of greenhouse gases. Through its agri-environmental functions, soil is both a storage site and a sink for organic carbon and is also a source of carbon dioxide (CO_2) emissions to the atmosphere, a high greenhouse gas, which has an influence on climate change (Bernoux et al. 2001, Hutchinson et al. 2007, Lal et al. 2007).

Soils are the largest terrestrial reservoirs of organic carbon (Yang et al. 2016). They contain about

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twice as much carbon as the atmosphere and are therefore a major compartment in the global carbon cycle (Xiong et al. 2014). Any change, positive or negative, in soil organic carbon stocks can represent a sink or source of atmospheric CO_2 (Yang et al. 2018). These stocks can be strongly modified by changes in practices or uses. They are also highly dependent on climate. Changes in land use within the agricultural sector (e.g., grassland turnover) and between agricultural and non-agricultural uses (afforestation, deforestation, urbanisation) impact soil carbon stocks and aboveground biomass. Urbanisation at the expense of generally agricultural land or natural areas contributes to the net greenhouse gas (GHG) emissions balance. Some previous studies that examined the effect of LULC on SOCS found that increasing urbanisation could lead to a loss of SOC due to artificialisation making soils non-permeable (Beesley 2012, Wei et al. 2014); while others research found that some urban soils had higher SOC contents than agricultural, grassland and forest soils (Golubiewski 2006, Raciti et al. 2011). Previous studies on the study area are few and have focused particularly on climate change, ecosystem degradation, water stress, and changes in LULC at different times (Ait Ouhamchich et al. 2018, El Jazouli et al. 2018, Barakat et al. 2019, Baki et al. 2021). However, no study has addressed the spatio-temporal modelling of SOCS in relationship to LULC change and environmental covariates. Such studies are needed, given the extent of land use change in the study area.

Remote sensing and spatial modelling based on deep learning and machine learning are techniques that have been more widely used in recent decades to quantify the spatio-temporal distribution of environmental variables such as LULC dynamics and soil organic carbon stocks (Bae et al. 2015, Shifaw, 2018, Yang et al. 2018, Obeidat et al. 2019, Fathizad et al. 2022). Many studies have deployed remote sensing techniques and spatial modelling to specifically assess LULC change and its potential impacts on soil organic carbon sequestration (Yan et al. 2015, Taghizadeh-Mehrjardi et al. 2017, Yang et al. 2018). They were able to show the important role of spatial remote sensing in modelling past and current growth knowledge to predict the future (Nurmiaty et al. 2014, Huong and Phuong, 2018). Thus, some artificial intelligence models have been used to try to predict LULC and SOCS transformations and their potential environmental effects. Baker (1989) and Muller and Middleton (1994) have abbreviated the most used models to assess LULC dynamics. Markov chain analysis and Multi-layer Perceptron (MLP) are easy-to-use artificial intelligence approaches to predict the spatial characteristics of LULC and SOCS based on current conditions (Sharjeel et al. 2016, Hazhir et al. 2018, Emadi et al. 2020, Kılıc et al. 2022). Furthermore, since these approaches offer the possibility to study historical changes, we adopted them to estimate and predict the rate of change of LULC types and the spatial distribution of SOCS in our study area between 1985 and 2050. Soil analyses were carried out to characterise soil physical parameters, including texture, density, and soil organic carbon content, while remote sensing and spatial modelling were used to estimate LULC changes and the spatial distribution of SOCS.

In the USA, Pouyat et al (2006) compared the variability of soil organic carbon stocks in six different cities and found that urban soils had the potential to sequester large amounts of atmospheric CO_2. Urban greenspaces contained higher SOC stocks than native grasslands, agricultural areas or forests in Colorado, USA (Golubiewski, 2006). Hutyra et al (2011) reported that above-ground carbon stocks in Seattle's urban forests were comparable to those in the Amazon rainforest. Kaye, McCulley and Burke (2005) measured aboveground net primary productivity in urban lawns and found it to be four to five times higher than in surrounding farmland and grasslands. In addition, Mestdagh et al (2005) found that the SOC stock of roads, waterways and grassy railways in urban areas accounted for 15% of the total SOC stock in a city. Soils under impervious surfaces in urban areas provided another often-overlooked source of SOC (Raciti et al. 2012, Edmonds et al. 2014).

In 2008, Morocco adopted the "Green Morocco Plan" as its agricultural and rural development strategy, which aims to promote Moroccan agriculture as a driver of economic and social development, while seeking to remove some of the many constraints on the sustainability of this development (Ministry of Agriculture 2008). The main objectives consist first in removing the constraint of spatial disparities, which are still significant and may even increase, due to unequal access to the means of agrarian development. The challenge of spatial planning and agricultural territorialisation, through development adapted to the conditions of each region by strengthening the assets of the various rural territories and correcting their weaknesses, can make it possible to respond. Among these weaknesses is the vulnerability of the land, which a policy of sustainable management and conservation can help to overcome. Secondly, the objectives of the 'Green Morocco Plan' aim to remove the constraint of the complex land tenure status of Moroccan lands, which is responsible for several forms of degradation, especially in state-owned lands and those with community status. This reform of the land tenure system aims to empower local actors in the conservation and rational management of natural resources (Ministry of Agriculture 2008).

The objective of this study is to assess the effect of LULC change on SOCS in the different classes (tree crops, cropland, urban area, unused land, and forest cover) while using LULC change monitoring which is important, especially when it results in inefficient and rapid urbanisation policy, unregulated, often uncontrolled urbanisation, often associated with threats to the SOCS. Rapid urbanisation, i.e., the growth of cities and infrastructure, extends to the surrounding land, which is usually natural areas, and this is usually associated with land and soil degradation. Land degradation is implicated in several major environmental problems such as soil erosion, landslides, biodiversity loss, increased atmospheric CO_2 concentration, desertification, and groundwater pollution (Townshend et al. 2012). Therefore, studies on LULC changes and their impacts on soil organic carbon stock are needed to achieve environmental sustainability. Spatial and temporal analysis of LULC trends and the relationships between the factors that lead to these variations would allow for better land use management. The main stages of this study are (1) mapping LULC in 1984, 2000 and 2018, (2) predicting LULC in 2018, 2030 and 2050, (3) soil sampling in the different LULC types to measure SOCS and soil texture, (4) spatial distribution of SOCS as a function of environmental covariates and (5) spatial autocorrelations between SOCS and environmental covariates.

2 MATERIALS AND METHODS

2.1 Study Area

The study area is in the Beni Mellal-Khenifra region of Morocco. It covers an area of 252,5 km^2 and a perimeter of 63,9 km^2, located at the junction of the High Atlas of Beni Mellal and Tadla plains (Figure 1). The altitude varies from 439 m in the northwest to 1709 m in the southeast of the study area. Administratively, it covers the municipalities of Sidi Jaber, Ouled M'barek, Adouz and Beni Mellal. The region has significant water resources from the Atlas Mountains. It also contains a large amount of fertile land (Ennaji et al. 2018, Barakat et al. 2019), making it a region with high agricultural production. Agriculture and livestock are the main sectors of economic activity and income. Olive and citrus are the main tree crops in the region. The climate of the Beni Mellal region is characteristic of a continental climate, with an average annual rainfall in this region of about 350-650 mm, of which almost 87% is received from October to March. In summer, Beni Mellal receives less rainfall than in winter. The average annual temperature is 14,17°C, with an average minimum temperature of 1,1°C observed in January and an average maximum temperature of 30°C in July and August. The average annual precipitation varies between 350-650 mm, of which about 87% is received from October to March.

The soils in the study area belong, in order of importance, to the following groups: Isohumous, brown subtropical or chestnut soils are by far the most widespread (Aghzar et al. 2002). They are found in the Tadla plain and cover nearly 83% of the irrigated area. These soils have a clayey or balanced texture and are favourable to agricultural development under irrigation. Brown calcimagnesic calcareous soils are

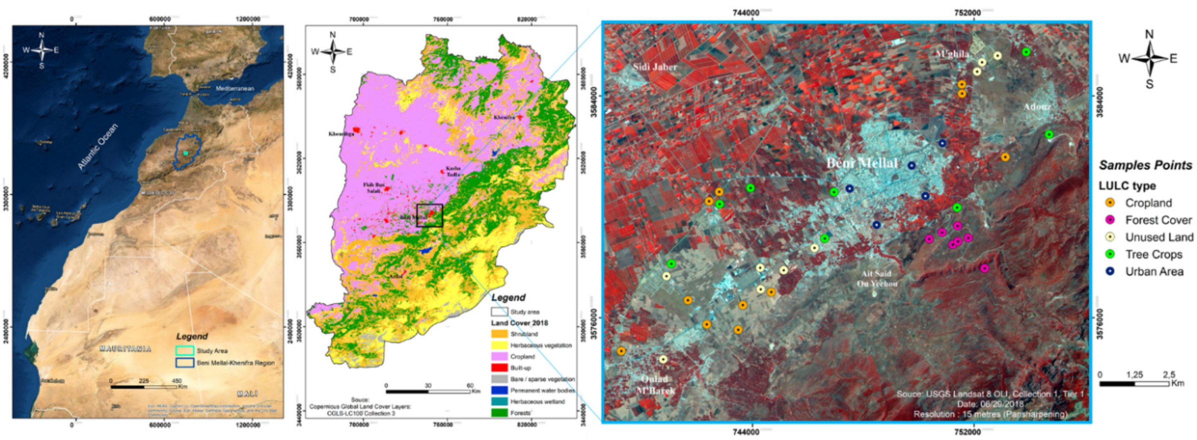

Figure 1: Location of the study area and soil sampling points.

shallow, very calcareous, and stony soils, but with a balanced texture. They are found along the wadis. These soils occupy 11% of the soil cover of the Tadla perimeter. The validation points presented in Figure 1 are mainly used to validate the LULC maps, and at the same time in each validation point, soil samples were taken to determine the soil organic carbon stock and texture of each LULC type.

2.2 Data and Methods

2.2.1 Data, Pre-Processing and Validation

In this study, the LULC maps from 1985, 2000 and 2018 were mapped using Landsat 5 TM (Thematic Mapper) and Landsat 8 OLI (Operational Land Imager) satellite images (earthexplorer.usgs.gov). The images have a ground resolution of 30 m, except for the IR (infrared) thermal band (band 6) having a resolution of 120 m for Landsat 5 TM images, and the panchromatic band (band 8) having a resolution of 15 m for Landsat 8 OLI images. All spatial data were defined on the same coordinate system, WGS_1984_UTM_Zone_29 N. All satellite images were taken during the dry season (4 July 1985, 13 July 2000, and 29 June 2018) to minimise errors caused by seasonal variations and seasonal effects of crops. The digital terrain model (ASTER GDEM) was taken on 23 September 2014 with a spatial resolution of 30 m (earthexplorer.usgs.gov). The selected temporal images were subjected to radiometric calibration (RC) and dark object subtraction (DOS) corrections. The raster images of the study area were subdivided according to a rectangular polygon created that covers the selected study area. Then, each raster image was classified to obtain the LULC maps. Field data and the Google Earth platform were used to identify the LULC classes, i.e., urban areas, forest cover, unused land, cropland and tree crops. The supervised classification method Spectral Angle Mapper (SAM) was used to obtain a broad level of classification, to derive all predefined LULC classes. The accuracy of the generated maps (1985, 2000 and 2018) was achieved for each land cover based on field observations and using 2018 "natural" colour RGB composition images from the WORLDVIEW-3 satellite with a resolution of 30 cm by viewing on the Google Earth platform. The Markov chain model was used to validate the detected changes and predict future LULC maps for 2018, 2030 and 2050. In the present study, the Markov transition matrix was applied to predict the 2018 LULC using the 1985 and 2000 LULC maps, and the 2000 and 2018 LULC maps were used to determine the LULC transition matrix for 2030 and 2050. For the model of validation, the simulated CA-Markov 2018 LULC was compared to the actual 2018 LULC map by image analysis.

2.2.2 Spectral Angle Mapper (SAM)

The SAM method is a supervised classification approach based on the measurement of the angular similarity between the spectrum of each pixel in the image and reference spectra, called endmembers (Hunter and Power, 2002). The latter can be measured directly in the field using a spectroradiometer, as well as extracted from the image. The assignment of an image pixel to a given class is based on the value of this angle "α" which measures the similarity or difference between the reference spectrum vector and its image counterpart (Girouard et al. 2004). Thus, the pixel will be assigned to the spectral class with which it has the most similarity, i.e., the smaller the angle "α", the greater the similarity between the spectrum of the evaluated pixel and the reference (Kruse et al. 1993). In our case, the prototype spectral signatures used to run the SAM were extracted from the image. They represent 5 severity classes (tree crops, cropland, unused land, urban areas, and forest cover). In this study, after visually testing and comparing the LULC results of six supervised classification algorithms (Support Vector Machine, Spectral Angle Mapper, Parallelepiped, Minimum Distance, Maximum Likelihood and Mahalanobis Distance), the SAM algorithm gave the best supervised classification result. The SAM algorithm was used to classify the five dominant LULC classes in the study area.

2.2.3 Soil Sampling and Analysis

The soil sampling sites were located by their GPS Coordinates and selected according to the LULC classes using the generated LULC map of 2018 (Figure 1). A total of 40 sites (8 points in tree crops class, 11 in cropland class, 9 in unused land class, 5 in urban areas and 7 in forest cover class) were sampled on 26/04/2019 and 03/05/2019 at a depth of (0- 15cm) in the absence of means to sample the entire soil profile. Each soil sampling site consisted of 3 intact soil cores using a metal cylinder 15cm high and 9cm in diameter for subsequent calculation of soil bulk density from the volume of the cylinder. All samples were dried in an oven at a temperature of 40°C for 2 days to a constant weight. The dry soil was sieved to 2 mm to separate pebbles >2 mm. Then the volume of the pebbles was measured to calculate the bulk density (BD). The fraction < 2mm was recovered and then crushed with an agate mortar to obtain a finer, homogeneous fraction that will be analysed for organic carbon content and soil texture.

$$BD = \frac{(\text{total dry mass} - \text{pebbles mass})}{(\text{total volume} - \text{volume of pebbles})} \quad (1)$$

Soil organic carbon (SOC) content was determined using soil organic matter (SOM) which was determined by the incineration method (loss on ignition or loss on fire). Loss on ignition is a direct measure of organic matter in the soil. The samples are placed in a muffle furnace at 540 °C for 4 hours. The loss by weight, after calcination, gives us the soil organic matter (SOM).

$$SOC = \frac{1.724}{SOM} \quad (2)$$

Where SOC: Soil organic carbon in % and SOM: Soil organic matter in %. After determining the soil organic carbon content, soil bulk density and volume of pebbles in the samples, we calculated the soil organic carbon stock using the following equation:

$$SOCS = SOC \times BD \times ST \times \frac{(1 - \text{pebbles})}{10} \quad (3)$$

Where SOC is the organic carbon content, BD is the bulk density and ST is the sampled thickness (15 cm). The SOC stocks for each LULC class in the study area were summarised according to the following equation:

$$\text{Total SOCS} = \sum_{i=1}^{n} (\text{SOC stock} \times \text{Si}) \quad (4)$$

Where Si is the area of the LULC type (in km^2).

Soil texture was determined by particle size analysis, which consists of separating the mineral part of the soil into categories classified according to the size of the mineral particles smaller than 2 mm and determining the relative proportions of these categories (sand, silt, clay), as a percentage of the total mineral soil mass. Textural classes were determined according to the USDA (United States Department of Agriculture) classification scheme (Garcia-Gaines, and Frankenstein, 2015).

2.2.4 Spatial Distribution of Soil Organic Carbon Stock

Satellite images obtained by Landsat 5 TM in 1985 and 2000, Landsat 8 OLI in 2018 were used to map the LULC, calculate vegetation indices and other remote sensing indices. After pre-processing the satellite images (part 2.2.1 radiometric and atmospheric corrections), a total of 4 vegetation indices were calculated. These indices include Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Ratio Vegetation Index (RVI), Enhanced vegetation index (EVI), Principal Component Analyses (PCA) and Minimum Noise Fraction (MNF) of spectral bands. As well as a digital elevation model (DEM) was used as a topography variable in the study area. In this study, a deep learning Multi-Layer Perceptron (MLP) model was fitted using 2018 data. To estimate historical and future changes in SOCS, the MLP model was applied to remote sensing data collected for the periods 1985, 2000 and 2018, as well as field data. MLP is the most important and commonly used artificial neural network (ANN) structure. It is a non-parametric estimator that can be used for SOCS regression (Taghizadeh-Mehrjardi et al. 2017). The basic processing elements in MLP are highly interconnected neurons. The neurons are organised in layers: an input layer, one or more hidden layers and an output layer. Data is fed into the network by the input layer, which sends this information to the hidden layers. The data is processed by the hidden layers and the output layer. MLP derives its capability from the non-linear processing in the hidden layers (Emamgholizadeh et al. 2018). In this study, the MLP model was developed to estimate SOCS by regression to a depth of 15cm using environmental covariates and measured SOCS data from the 40 sampled and analysed sites. The environmental covariates and colour compositions images (red-green-blue RGB and near-infrared-green-blue NirGB) were integrated into the MLP model as images of the independent variables, while the SOCS measurements were integrated as the dependent image after their spatial interpolation by the Kriging method.

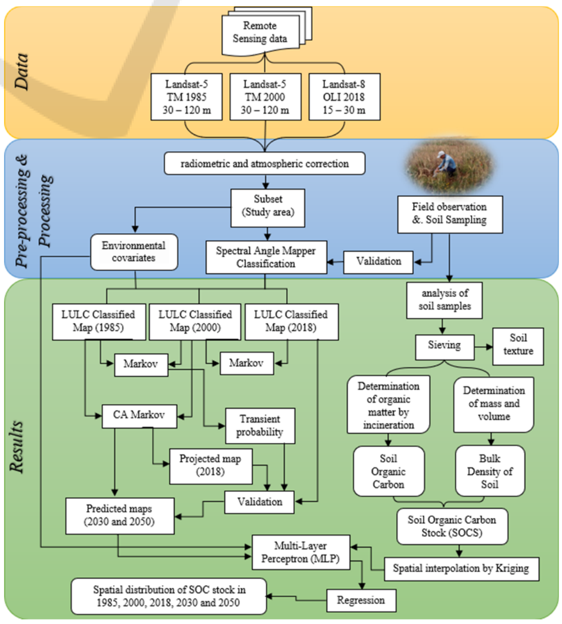

Figure 2: Flow chart of the working methodology.

3 RESULTS AND DISCUSSION

3.1 LULC Change Analysis

The LULC maps (1985, 2000, 2018) obtained by the SAM supervised classification method of Landsat 5 TM and Landsat 8 OLI data are presented in Figure 3, along with their projections to 2018, 2030, and 2050 obtained by the CA-Markov geosimulation model. These mapping results show current and future changes in five dominant LULC classes in the study area. These mapped LULC classes include five LULC types: Unused Land (Ivory colour), Forest Land (Purple colour), Urban Area (Midnight Blue colour), Cropland (Beige colour), and Tree Crops (Green colour).

Statistical analyses of the LULC maps (Table 1 and Figure 3) revealed that tree crops have increased significantly in the study area. They have evolved from 11,6% (29,3 km^2) in 1985 to 18% (45,5 km^2) in 2018 with a positive rate of change of 55,3%. According to the projection in 2050, tree crops would be 18,2% (46 km^2) with a rate of change of 1,1% between 2018 and 2050. This transition is linked to the Moroccan Ministry of Agriculture's tree sector support program (Green Morocco Plan), which aims to remove the constraint of the complex land tenure status of Moroccan lands, responsible for several forms of degradation, particularly in state lands and those with community status. This reform of the land tenure system aims to empower local actors in the conservation and rational management of natural resources.

On the other hand, the statistics provided in Table 1 show both regressive and progressive changes in the LULC natural units in the study area. We can see a slight increase in forest cover from 6,4% (16,2 km^2) in 1985 to 6,8% (17,1 km^2) in 2018. The cropland has decreased remarkably, from 68,9% (173,7 km^2) in 1985 to 37,6% (95 km^2) in 2018. Based on this regressive trend, cropland in the study area could decrease to 33,9% (85,5 km^2) in 2050 with a negative rate of change of -10% between 2018 and 2050 according to CA-Markov based projections. Comparing the area gains and losses between cropland and each of the other LULC classes over this period, the most significant conversion of cropland was to urban areas and unused land. This main conversion of cropland contributing to the decline of fertile soils in the study area could be explained by the rapid increase in urbanisation and drought. A true conversion of cropland to urban areas around the city of Beni Mellal was also observed between 1985 and 2018, which would be due to urban and suburban growth and expansion. Urban areas increased from 1,8% (4,5 km^2) in 1985 to 10,7% (27,1 km^2) in 2018 with a positive change rate of 502,2%. Simulations based on CA-Markov show that urban areas would reach 16,3% (41,1 km^2) with a rate of change of 51,7% between 2018 and 2050. This increase in urban areas during the study period (1985-2018) is related to the conversion of a portion of cropland into built-up areas due to urban sprawl and expansion of economic development activities. At the same time, unused land increased from 11,3% (28,5 km^2) in 1985 to 26,9% (67,8 km^2) in 2018 with a positive rate of

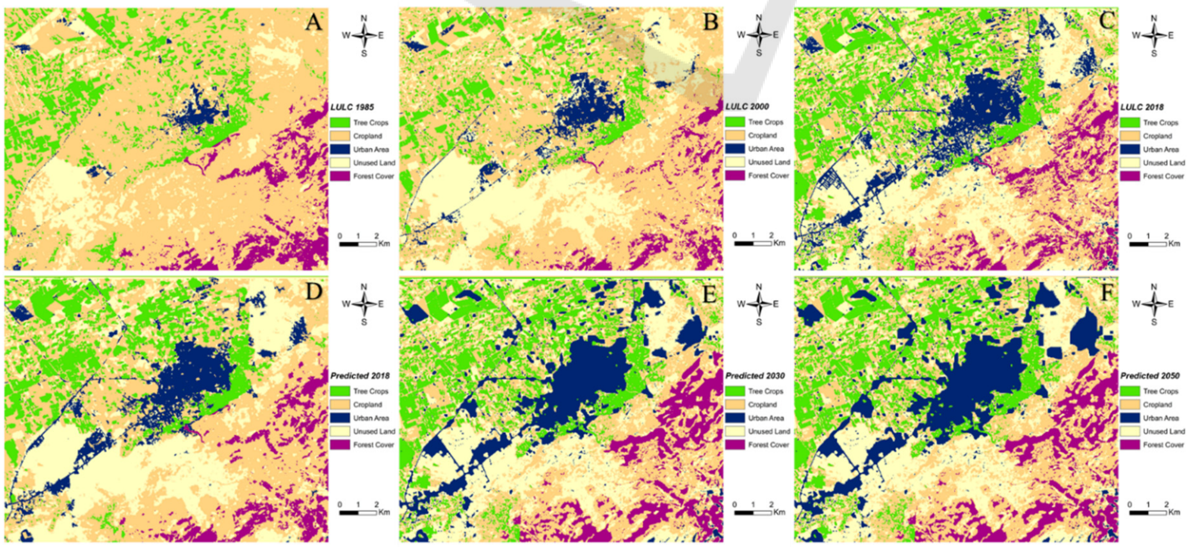

Figure 3: Observed LULC maps for: (A) 1985, (B) 2000, (C) 2018 real (D) 2018 predicted, (E) 2030 predicted and (F) 2050 predicted.

Table 1: Change area in different LULC categories between 1985 and 2050.

Type of Land Use	Surface									
	1985		2000		2018		2030		2050	
	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)
Tree Crops	29,3	11,6	23,2	9,2	45,5	18	46	18,2	46	18,2
Cropland	173,7	68,9	139,4	55,3	95	37,6	86,4	34,2	85,5	33,9
Urban Area	4,5	1,8	11,6	4,6	27,1	10,7	36,6	14,5	41,1	16,3
Unused Land	28,5	11,3	67,5	26,8	67,8	26,9	61,7	24,4	59,2	23,5
Forest Cover	16,2	6,4	10,5	4,2	17,1	6,8	21,8	8,6	20,7	8,2
Total	252,2	100	252,2	100	252,5	100	252,5	100	252,5	100
Type of Land Use	Change									
	1985-2000		1985-2018		2018-2030		2018-2050			
	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)		
Tree Crops	-6,1	-20,8	16,2	55,3	0,5	1,1	0,5	1,1		
Cropland	-34,3	-19,7	-78,7	-45,3	-8,6	-9,1	-9,5	-10		
Urban Area	7,1	157,8	22,6	502,2	9,5	35,1	14	51,7		
Unused Land	39	136,8	39,3	137,9	-6,1	-9	-8,6	-12,7		
Forest Cover	-5,7	-35,2	0,9	5,6	4,7	27,5	3,6	21,1		

change of 137,9%. This change would reach 23,5% (59,2 km^2) in 2050 with a rate of change of -12,7%. The increase in unused land is linked to the conversion of agricultural land to urbanised areas in the future (public facilities, industrial areas, urban areas, and rural areas) and could also be explained by the droughts during the last decades.

3.2 Organic Carbon Stocks and Soil Texture of LULC Types

Analytical data on SOC stocks and texture of soils sampled in different LULC classes in the study area are presented in figures 4 and 7. Summary statistics in terms of min, max and mean for the analysed parameters (SOC and SOCS) are provided in Figure 4.

Soil organic matter and soil organic carbon is rich in forests and unused or infertile land because: (1) Forests and unused soils are less disturbed than agricultural soils. (2) Forests and unused soils evolve slowly. Nevertheless, their fertility is limited and strongly dependent on the natural flows of elements and organic matter. (3) Forests and unused soils are generally the poorest soils chemically or those with physical properties most unfavourable to agriculture. In contrast to agricultural soils, they are not worked or are only lightly worked. This results in a high accumulation of organic matter in the litter and surface soil horizons.

Traditionally, SOC in forest ecosystems is usually considered in the regional assessment. As shown in this study (Figure 4), the organic carbon content at a depth of 0-15 cm in forest soils (4,9% - 10,4%) was higher than that reported for urban soils in the Tadla plain (3,4% - 7,2%), where the city of Beni Mellal is located. This showed that forest soils can store large amounts of organic carbon in the soil. Soil organic carbon contents measured under different types of LULC varied in the following order: forest cover > unused land > urban areas > cropland > tree crops. A variation in SOC is very noticeable in urban soils mainly due to human activities that often change the parameters of these soils.

SOC stocks were calculated for each sample in the study area using the organic matter, bulk density, and pebble volume values in the sample. In Figure 4, SOCS values in soils sampled at a depth of 15cm covering the whole study area ranged from 4,7 to 11,7 kg/m^2. The SOCS in the forest cover ranged from 8,1 to 11,7 kg/m^2, with an average of 9,9 kg/m^2. In cropland, the SOCS varied between 5,8 and 10,1 kg/m^2 with an average of 7,9 kg/m^2, while the SOCS stocks in tree crops varied between 4,7 and 8,9 kg/m^2 and an average of 6,4 kg/m^2. Unused land had SOC stocks between 7,6 and 10,1 kg/m^2 with an average of 8,9 kg/m^2. At the same time, urban areas had SOC values between 5,8 and 9,2 kg/m^2 with an average value of 7,4 kg/m^2. From these results of the sampled soils, we notice that the SOC stocks measured under different types of LULC varied in the following order: forest cover > unused land > cropland > urban areas > tree corps.

3.2.1 SOCS of the Study Period

The SOC stocks for 1985, 2000, 2018, 2030 and 2050 were calculated for each LULC type in the study area using the average SOCS values and the area of each LULC type. In Table 2, the SOCS values have been summed separately for each date and LULC type. These SOCS have changed slightly in the forest cover

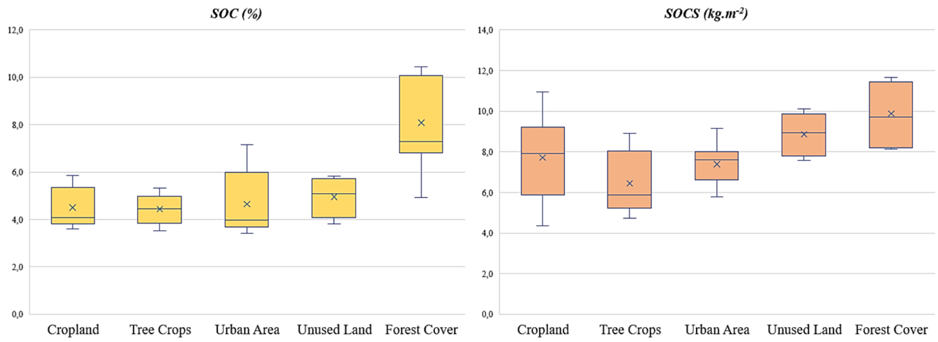

Figure 4: Variation in SOC and SOCS by LULC type.

Table 2: Change in SOCS by LULC type between the years 1985, 2000, 2018, 2030 and 2050.

Type of Land Use	SOCS (kg/m²)					SOCS Change (kg/m²)		
	1985	2000	2018	2030	2050	1985-2018	2018-2030	2018-2050
Tree Crops	187,5	148,5	291,2	294,4	294,4	103,7	3,2	3,2
Cropland	1337,5	1073,4	731,5	665,3	658,4	-606	-66,2	-73,1
Urban Area	33,3	85,8	200,5	270,8	304,1	167,2	70,3	103,6
Unused Land	253,7	600,8	603,4	549,1	526,9	349,7	-54,3	-76,5
Forest Cover	160,4	104	169,3	215,8	204,9	8,9	46,5	35,6

class from 160,4 kg/m^2 in 1985 to 169,3 kg/m^2 in 2018 with a positive rate of change of 8,9 kg/m^2. According to the projections in 2050, the SOCS would expect 204,9 kg/m^2. At the same time there is a net increase in these stocks in the tree crops class from 187,5 kg/m^2 in 1985 to 291,2 kg/m^2 in 2018, with a rate of change of 103,7 kg/m^2. In 2050, these stocks are projected to be 294,4 kg/m^2. This slight increase in SOCS in the tree crop and forestry sectors is mainly due to the planting of fruit trees in the plains and afforestation in the forests that have been carried out under the two strategies (the Green Morocco Plan and the National Watershed Management Plan). These two strategies are carried out mainly to combat the degradation of natural resources (soil, water, forests, etc.) and to combat erosion to increase organic carbon stocks in the soil.

Similarly, we can notice a strong increase of SOCS in unused land from 253,7 kg/m^2 in 1985 to 603,4 kg/m^2 with a rate of change of 349,7 kg/m^2. This increase could be explained by the increase of unused land surfaces during this period due to the drought. However, there is a strong decrease in the SOCS of cropland from 1337,5 kg/m^2 in 1985 to 731,5 kg/m^2 in 2018 with a negative rate of change of -606 kg/m^2. Based on this regressive trend, cropland SOCS could decrease to 658,4 kg/m^2 in 2050 with a negative rate of change of -73,1 kg/m^2. This decrease is generally due to the extension of urbanisation, the increase of informal settlements on the outskirts of the city of Beni Mellal (Adouz, M'ghila, Ourbiaa...), and to drought and water stress which convert the surfaces of croplands to unused lands.

Moreover, in urban soils, SOCS has increased from 33,3 kg/m^2 in 1985 to 200,5 kg/m^2 in 2018 with a positive variation of 167,2 kg/m^2. In 2050, according to projections, these stocks in urban soils would reach 304,1 kg/m^2. According to Pouyat et al in 2006, urban soils have the potential to sequester large amounts of atmospheric CO_2. Similarly, Golubiewski in 2006 found that urban green spaces contained higher stocks of SOC than native grasslands, agricultural or forested areas in Colorado, USA.

The results show that there is a significant difference between the SOCS of different types of LULC. LULC play a dominant role in influencing SOC content and stock because surface soil disturbance, litterfall and decomposition vary with LULC, resulting in a difference in SOCS according to land use. The SOCS of forest soils is very high compared to other LULC due to the intense topography and forest cover, which slows down soil erosion and organic carbon decomposition, resulting in forest soils having SOCS and SOC above their potential capacity. However, the SOCS of tree crops and cropland is very low compared to forest cover and unused land due to intensive agricultural cultivation (tillage), which accelerates soil erosion and decomposition of soil organic carbon (Lal, 2005, Laganière et al. 2010).

3.2.2 Soil Organic Carbon Trends for 1985, 2000, 2018, 2030 and 2050

To spatially distribute the content of SOC stocks between 1985 and 2050, spatial regression maps of these stocks from different environmental covariates (DEM, NDVI, EVI, RVI, SAVI, LULC, MNF, PCA, RGB, NirGB) were generated using a deep learning approach with MLP (Figure 5). The maps were plotted at the same scale and with geometric intervals to facilitate comparisons. The results indicated that SOC stocks showed high spatial variability in the higher elevations of the study area. From the results obtained concerning the stock of SOC, we deduce that the important factors affecting this stock are the topography of the place, the uses, and the types of soil. In addition, the fact that photosynthesis allows through biomass to store carbon in the soil, which we see in Figure 5 concerning the forest where there is an increase in the stock of SOC according to the years 1985, 2000, 2018 and 2050. Similarly, SOCS are more sensitive to growth and increasing population density (Lal and Augustin, 2011, Liu et al. 2016). Urbanisation and buildings in the study area degrade soils, cementing them and making them impermeable, and thus they cannot absorb carbon circulating in the biosphere. Thus, agricultural soils and unused land transformed over time into built-up areas could increase the loss of soil carbon sinks. This indicates that land use has had an impact on the distribution characteristics of SOC in the topsoil (0-15 cm) of the study area (Figure 5).

The spatial distribution of SOCS (in 1985, 2000, 2018, 2030 and 2050) is shown in Figure 5 and shows that high SOCS levels generally correspond to forests. The spatial distribution of SOCS is almost similar for each date across the different covariates and LULC types. Overall, SOCS stocks in the south-east are higher than those in the north-west, east, and west of the study area, respectively. The results show small pockets of SOCS highest in the central and extreme south-eastern corner at a depth of 0-15 cm, which corresponds to unused land in the Tadla plain and forest cover in the mountains. The eastern and western corners of the study site have the lowest SOCS value as it is covered by urban areas, cropland, and tree crops. This indicates that forests and grasslands are more efficient in storing SOC than other types of LULC. Most of the study area has average SOCS values. The analysis suggests that, mainly in the topsoil (0-15 cm depth), the spatial distribution pattern of SOCS was highly variable due to small-scale variations in supply, redistribution, and stabilisation. The central part of the study area is represented by a low SOCS.

The multi-date (1985, 2000 and 2018) spatial autocorrelations of SOCS with environmental covariates derived from satellite images are presented in Figure 6. In this analysis, SOCS derived from spatial interpolation techniques (IDW and Kriging) and MLP were autocorrelated with spectral indices (NDVI, EVI, RVI, SAVI), image transformation indices (MNF, PCA), LULC units and spectral bands (RGB and NirGB). The analysis shows very high autocorrelations between the vegetation indices and the SOCS. However, these autocorrelations are particularly higher for the SOCS derived from spatial modelling with MLP than the SOCS derived from

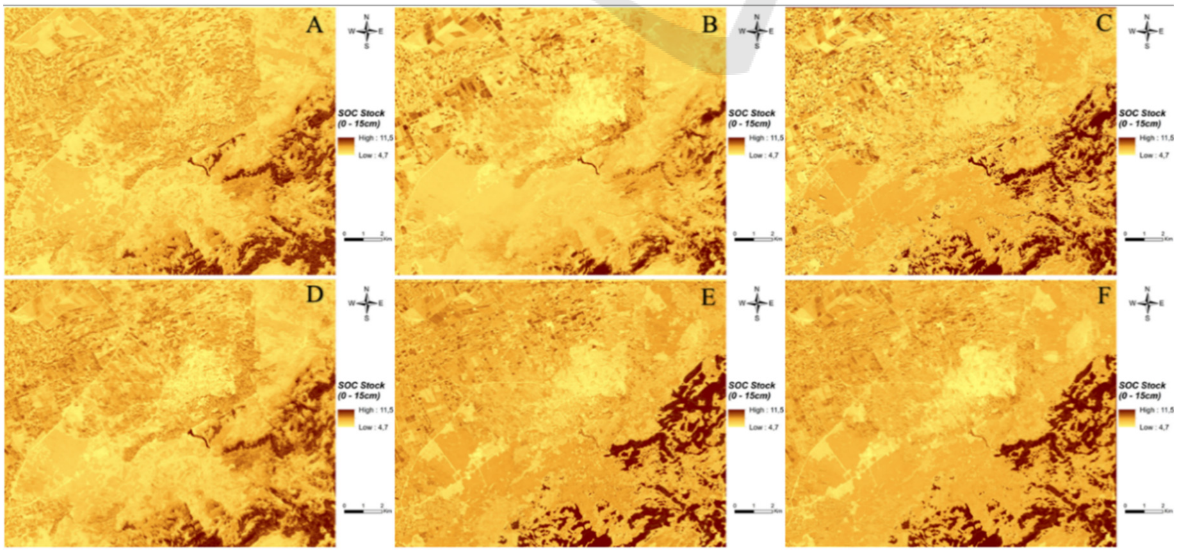

Figure 5: Predicted soil organic carbon stocks (SOCS) (in kg/m^2) maps for (A) 1985, (B) 2000, (C) 2018 real, (D) 2018 predicted, (E) 2030 and (F) 2050.

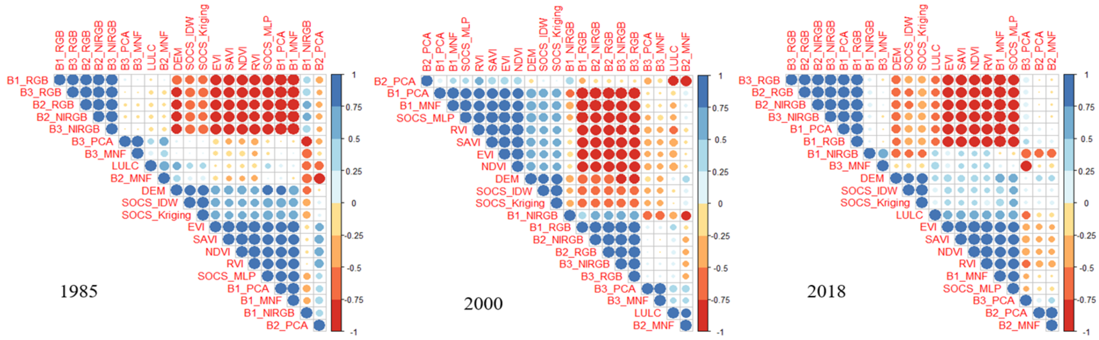

Figure 6: Spatial autocorrelations between SOCS and environmental covariates.

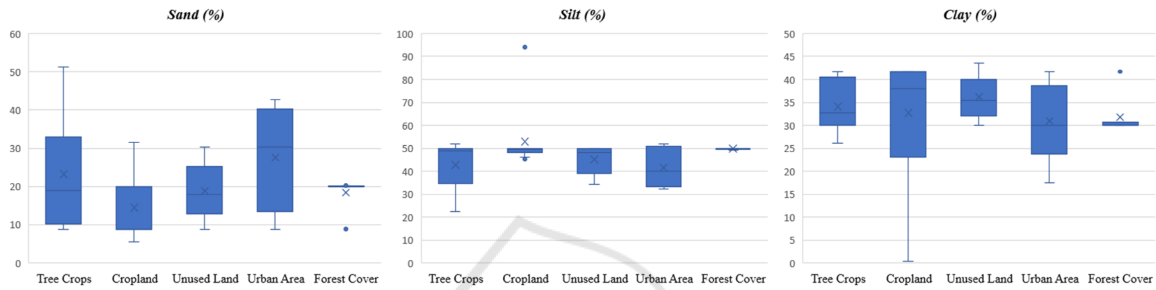

Figure 7: Variation in the percentage of Sand, Silt and Clay by LULC type.

spatial interpolation techniques. This suggests that spatial modelling approaches to SOCS with deep learning algorithms from environmental covariates and in situ measurements are more accurate than univariate spatial interpolation techniques based on field samples. Similarly, significant, and positive spatial autocorrelations were observed with the topographic variable, but very high negative autocorrelations were observed with the spectral bands and SOCS for all three dates. In contrast, the relationship between LULC units and SOCS from the three approaches is particularly variable depending on the multi-date dynamics of LULC. The autocorrelations between SOCS and LULC units are very weak in 1985 and 2000 but significant for the year 2018. This suggests that the land use dynamics in the area have favoured SOCS.

3.2.3 Soil Texture

Texture indicates the relative abundance of different particle sizes in the soil: sand, silt, or clay. Texture determines how easily the soil can be worked, how much water and air it contains, and how quickly water can enter and move through the soil. Soil texture is very stable over time and less affected by LULC. In addition, soil aggregates are a factor responsible for SOC stabilisation (micro-aggregates protect the SOC in the long term and the renewal of macro-aggregates is a crucial process that influences SOC stabilisation) (Six et al. 2004). Therefore, the texture analysis of the sampled soils was performed by adopting the USDA classification (Garcia-Gaines, and Frankenstein, 2015). The forty sites sampled for each type of LULC have clay values ranging from 0,3% to 41,7%, sand values ranging from 5,6% to 51,4%, and silt values ranging from 22,5% to 94,1% (Figure 7). In the study area, the textural class of the studied soils is **clay loam** for the LULC classes of tree crops and urban areas and **Silt-clay loam** for the classes of cropland, unused land, and forest cover. The results of the particle size analyses projected onto the USDA triangular diagram showed that all LULC types have a **loamy** soil texture which is a moderately fine texture of fine sands and silts.

4 CONCLUSIONS

In this study, a multi-date geospatial approach to soil organic carbon stocks in the Beni Mellal region of Morocco and its relationship with LULC dynamics and environmental covariates was developed by applying two methods: a spatial interpolation method on in situ measurements and a MLP model trained on ten biophysical variables. For the three dates considered (1985, 2000 and 2018), the results obtained show highly significant spatial autocorrelations (R^2>0,75) between the SOCS from the multivariate modelling with the MLP better than those obtained between the SOCS from the spatial interpolation techniques (IDW and Kriging). On the other hand, spatial autocorrelations between LULC units and SOCS are highly variable across years. For the earliest years (1985, 2000), very low autocorrelations were found between the SOCS and LULC units, but the most the recent year 2018 was distinguished by significant positive correlation values between the SOCS from the MLP modelling and the LULC units. Indeed, land use change in the study area between 1985 and 2018 was (11,6% to 18%), (68,9% to 37,6%), (1,8% to 10,7%), (11,3% to 26,9%) and (6,4% to 6,8%) for tree crops, cropland, urban area, unused land, and forest cover respectively. In general, urbanisation linked to population growth has also had a significant impact on LULC change and has tended to implicitly reduce soil carbon sequestration. However, according to the SOCS results, tree crops, unused land and forest cover mainly tend to be more resistant to land degradation. Furthermore, it should be noted that this study was conducted at a very small spatial scale with few samples. A large-scale comparative evaluation of multivariate SOCS geospatial approaches based on deep learning or machine learning and spatial interpolation techniques is one of the perspectives for future studies to refine the different conclusions from this approach.

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