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Research Article

Patterns of Soil Nitrogen Sequestration in Drylands Explored with Pedotransfer Functions and Bayesian Analysis

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Abstract: The stock assessment of organic carbon and total nitrogen in the soil in addition to their relationships with site characteristics is of major importance whether at local, regional or global scale. The improvement of pedotransfer functions for these stocks evaluation in soils is a key for sustainability of agro-systems, especially in erodible systems of Mediterranean semi-arid areas. This work aimed to study relationships between total nitrogen stocks and other physico-chemical properties of clayey and sandy soils of Tunisian database and to do this, we used pedotransfer functions and structural equations modeling. For modeling total nitrogen stocks, two Tunisian soil databases composed from 450 horizons of clayey soils and 602 horizons of sandy soils were used. The optimal models of nitrogen stocks were given by two significant pedotransfer functions: (i) that of clayey soils with a standard error of prediction of 18.51 and associated p-value of 0.000 and (ii) that of sandy soils with a standard error of prediction of 5.76 and associated p-value of 0.016. Then, we perform a path analysis using structural equations modeling and Bayesian analysis to investigate simultaneously the interactions between the different components of the soil properties and their relationships with total nitrogen stocks. Results show that, in both soil types, the stock of total nitrogen is always controlled in the same way; it is significantly linked to chemical properties and bulk density more than by physical properties. The root mean square errors of the approximations were 0.080 and 0.043 for the clayey and sandy models, respectively.

Keywords: Mediterranean region, modeling, nitrogen stock, path analysis

INTRODUCTION

The importance of an understanding of the national levels of Organic Matter (OM) is reinforced by the statements of the Framework Convention of United Nations on Climate Change (UNFCCC) signed at Rio de Janeiro in 1992. In fact, the UNFCCC aims to stabilize greenhouse gas concentrations in the atmosphere at a level that limits adverse impacts on the global warming. Their Articles 3.3 and 3.4 describe the potential mechanisms which can reduce the emissions and the choice of activities that can increase terrestrial sinks (Smith, 2004). There are clear linkages between the United Nation Convention to Combat Desertification (UNCCD) and the UNFCCC. One of the most evident linkages concerns the soil Organic Matter (OM) status (Brahim *et al*., 2012). The stabilization of increasing N_2O and CO_2 concentration in the atmosphere is the major ecological concern of the world (Mishra *et al*., 2010). In fact, knowing the sequestration potential allows preserving the soil conservation and especially helps strengthen the "wells function" of soil and to offset anthropogenic emission of greenhouse gases. Organic Matter (OM), as transversal indicator, is a major determinant of soil fertility, water holding capacity, biological activity and is highly correlated to levels of above- and below-ground biodiversity. OM also influences structure, friability and aggregation of soil, which have major implications for its permeability and erodibility. The level of OM can, therefore, be a robust indicator of the degradation of a soil system (Brahim *et al*., 2012). Soil OM is a key element of some terrestrial ecosystem and any variation in its abundance and composition has significant effects on several of the processes that occur within the system (Batjes, 1996). The organic stock (carbon and nitrogen) is influenced by vegetation, soil types, climatic conditions and topography (Bedison and Johnson, 2009). Vegetation is the main source of soil OM. For this reason, land uses are known to play a major role in organic stocks build up through organic matter input (Pandey *et al*., 2010) in different depths (Batjes, 1996; Bernoux *et al*., 2002; Brahim *et al*., 2010) and

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bioclimatic zones into soils through the processes of soil aggregation (Brahim *et al*., 2011a).

Global stocks of soil nitrogen are estimated at 133-140 Pg of N (1 Pg = 10^{15} g) for the upper 100 cm (Batjes, 1996). In arid zones, soils are already poor to very poor in organic matter and are naturally unstable and easily eroded. Though "azote", the French name for nitrogen given by Lavoisier, means "lifeless" and inert, this element is a major constituent of living organisms which catalyze key steps in biogeochemical cycling (Pansu *et al*., 1997). Nitrogen is a remarkable element; the vegetative growth of plants (leaves, stems and roots). The soil fertility is especially N dependent, the nitrogen problem is particularly crucial under arid soil conditions. As a result of a too low supply of total nitrogen, coupled with the relatively small fraction there of which is rendered available by plants, nitrogen poverty with its various manifestations is one of the prominent problems of soil fertility in Tunisia and especially in soils of arid and semi-arid Northern Africa areas. Many of these soils are situated in regions of high winter rainfall (extreme northwest) and produce an abundant spring growth; hence their nitrogen-content, owing to the large supply of decaying OM, may compare very favorably with that of an average soil of the humid region. In the Maghreb arid soils, however, which receive only 350 mm of rain per year or less, it is quite usual to find concentrations of total nitrogen below 0.01% in the air-dried surface soil. To do this, starting from the arid climatic conditions and meager vegetation that influence this low rate of nitrogen in the soil, it remains to study the effect of soil type on the stock of this important and vital element. Nitrogen was predicted by different biochemical properties (Trasar-Cepeda *et al*., 1998). The biochemical properties are also closely related to physical and especially chemical soil properties because of the dynamic and interactive nature of soil processes (Schoenholtz *et al*., 2000).

Many efforts have been made in research on the status of organic stocks in the soil and improved procedures for interpreting results. In recent decades, simple or multiple regressions models or Pedotransfer Functions (PTFs) and the Structural Equations Modeling (SEM) based on easily measurable soil properties are a suitable tool for the explanation. Studies of organic carbon stocks and total nitrogen in the Tunisian soils (Ibrahim *et al*., 2009; Brahim *et al*., 2011a) have determined the stocks in each soil type, the total stock in the country and finally mapped and compiled the maps for the OC and TN. However, variables and factors affecting these stocks are well known, especially with regard to stock of total nitrogen. This study has two objectives:

- To establish a model using PTFs based on different soil physical and chemical properties, in sandy and clayey soils from Tunisia
- To build models using SEM, in order to estimate the real variables except the soil cover in these drylands

MATERIALS AND METHODS

Study area: Tunisia situated in North Africa and in south of Mediterranean Sea between the latitudes 32° and 38° North and between the longitudes 7° and 12° Est. It is located at the junction of the western and oriental Mediterranean and covering a surface of 164000 km^2, of which more than 67% are under semi-arid and arid climate and the rest are under sub-humid and humid climate (Fig. 1). In spite of this small surface, nor the climate neither the vegetation are uniform. In fact, the geographical position and the general orientation of the topography are influenced at the North by the Mediterranean Sea and at the South by the Sahara. Concerning the Center, it is under the conjugated effect of these two elements. Even the

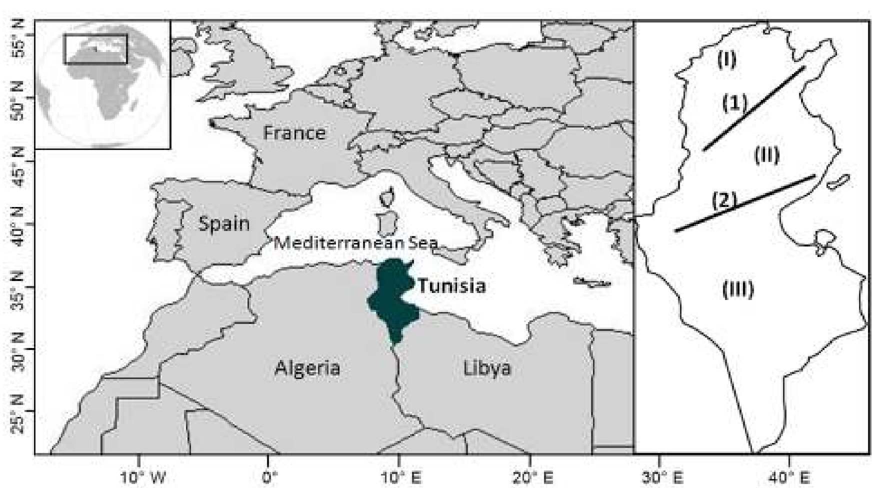

Fig. 1: Location of Tunisia in the Mediterranean Sea and localization of the bioclimatic zones: zone (I) zone (II) and zone (III); (1) dorsale; (2) gafsa-sfax line

dominance of calcareous rocks, geology consists of large range of type of rocks. It has for consequence an enormous variety of soils which can be regrouped in nine big classes (Brahim *et al*., 2010). At the same time Mediterranean and Saharian country, Tunisia shows several soil resources that relates the importance of the climatic and morphological effects on its physiography. From North to South, the country shows remarkable variation in organic matter content, going from 20% in the humid and sub-humid bioclimatic stages with dense vegetation, until 0.3% in the arid and Saharian bioclimatic stages with skinny and little abundant vegetations, except of the oases where the contents are relatively raised due to the artificial organic contributions (Brahim *et al*., 2011a). Pragmatically, the sampling is consisted of layer of soil, for the superficial slice 0-30 cm depth.

Three main areas characterized the country:

- The northern zone has three sub-climates; the humid, the sub-humid and the semi-arid.
- The center zone is characterized by the semi-arid and arid climates, limited at the north by the Dorsale (mountain range system) (1) and spreads until the line of Gafsa-Sfax (2).
- The southern zone has an arid and Saharian climate, spreads from the south of the mounts of Gafsa until the confines of the Sahara (Fig. 1).

Soil sampling: Soils were sampled during the two years 2007-2009 in various climate and land use conditions. A total of 1052 soil samples were collected from 124 sampling sites, covering all types of land use. For modeling TN stocks, the samples were divided in two databases clayey and sandy soils including 450 and 602 soil horizons, respectively. At each site, samples were collected at 0-30 cm depths.

Laboratory analysis: The samples were transported to the laboratory and a part of soil passing through the 2 mm sieve was used for analysis. The soil organic carbon content was determined by Walkley-Black method. The Total Nitrogen (TN) content was determined by Kjeldahl digestion method. The soil pH was measured in distilled water with dry soil by a pH-meter. The soil bulk density (D_b) was determined as the dry weight per unit volume of soil core (cylinder method) after a 12 h drying in an oven at 105°C. The granulometric fraction were calculated after soil dispersion with sodium hexametaphosphate (Robinson pipette method): clay (particle 0-2 μm), silt (fine and coarse 2-50 μm) and sand (fine and coarse; 50-2000 μm) are calculated in percent. Calcium carbonate ($CaCO_3$) content was determined by Bernard calcimeter method. All procedures used for the soil analysis are detailed in Pansu and Gautheyrou (2006).

Data analysis:

Pedotransfer Functions (PTFs) or Multiple Linear Regressions (MLR): Predictive equations using simple or multiple regressions (also named Pedotransfer functions-PTFs) were generally developed within one specific soil unit and/or for specific ecosystem (Wang *et al*., 2012).

MLR constitutes an accurate tool to evaluate soil quality, since it generates a minimum data set of indicators. MLR have been successfully used by different authors to evaluate soil quality, being used in natural forest soils balanced with the overall environment (Trasar-Cepeda *et al*., 1998) or in agriculture soils under different management (Lentzsh *et al*., 2005; Bernoux *et al*., 1998; Brahim *et al*., 2012). The objective of the present work is: firstly, to establish a models using MLR based on different soil physical and chemical properties, in different zones from Tunisia, so that we can searched equations ($N = \beta 0 + \beta 1\ X1 + \beta 2\ X2 + ... + \beta n\ Xn + \varepsilon$. where, N is the dependent variable and X1, X2,…. Xn the independent variables as well as the soil physical and chemical properties) for both groups of soils. Then, all the variables would be included simultaneously into single model in order to test the interactions between the independents variables as well as their contributions on the dependent variable.

The procedure used was a stepwise linear regression, which allowed independent variable to be individually added or deleted from the model at each step of the regression. The MLR method was used because it is a practical tool that furnishes direct quantitative results and also because the data set was not adapted to spatial analysis such as geostatitics due to lacking or imprecise geographic coordinates.

In the linear regressions, only parameters with statistical significance at the 0.01 significance level were considered for computing predictive equations and reporting results. Standard Error of the Prediction (SEP) and percentage of variance explained, through R^2 values, were used as means to evaluate the reliability of the models. All the statistical analyses were conducted using the SPSS 16.0 software. The optimal models of nitrogen stocks are obtained by PTFs combined with Principal Component Analysis (PCA) to eliminate multicollinearity among variables (Wang *et al*., 2012).

Structural Equation Modeling (SEM): Structural Equation Modeling (SEM) is a statistical methodology that takes a confirmatory approach to the analysis of a structural theory bearing on some phenomenon. Typically, this theory represents "causal" processes that generate observations on multiple variables (Bentler, 1989, 1990, 1992). The structural equation modeling

Table 1: Summary of indicative thresholds adjustment tests of SEM

Abréviation	Fit index	Stringent thresholds levels	Acceptable threshold levels for complex models	References
χ^2/df	Chi-square/degrees of freedom	<2 or 3	<5	Wheaton *et al.* (1977) and Tabachnick and Fidell (2007)
GFI	Goodness of fit index	>0.9	>0.95	Tabachnick and Fidell (2007)
AGFI	Adjusted goodness of fit index	>0.8	>0.95	Tabachnick and Fidell (2007)
PGFI	Parsimony goodness of fit index	<0.5	>0.90	Mulaik *et al.* (1989) and Crowley and Fan (1997)
NFI	Normed fit index	>0.8	>0.95	Hu and Bentler (1999)
TLI	Bentler-Bonett non-normed fit index or NNFI	>0.9	>0.95	Sharma *et al.* (2005)
RFI	Relative fit index	>0.9	>0.80	Hu and Bentler (1999)
IFI	Incremental fit index	>0.9	>0.80	Miles and Shevlin (2007)
CFI	Comparative fit index	>0.9	>0.95	Hu and Bentler (1999)
RMR	Root mean square residual	<0.05	<0.08	Hu and Bentler (1999)
RMSEA	Root mean square error of approximation	<0.06 or 0.07	<0.09 or 0.1	MacCallum *et al.* (1996) and Steiger (2007)

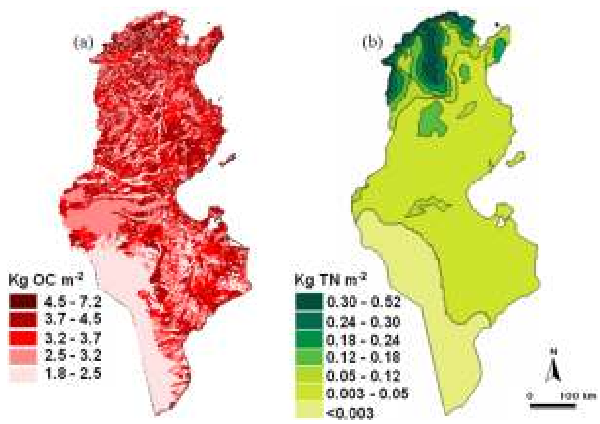

Fig. 2: Maps of Tunisian soil organic stocks in 0-30 cm depth, (a) map of soil organic carbon stock (Brahim *et al*., 2011a), (b) map of soil total nitrogen stock (Ibrahim *et al*., 2009)

conveys that the causal processes under study are represented by a series of structural equations. And that these relations can be modeled. The model can then be tested statistically in a simultaneous analysis of the entire system of variables to determine to which it is consistent with the data.

Several aspects of SEM set it apart from the older generation of multivariate procedure (Fan *et al*., 1999). First, as noted earlier, it takes a confirmatory, rather than an explanatory, approach to the data analysis (although aspects of the latter can be addressed). Furthermore, by demanding that the pattern of inter variable relations be specified a priori, SEM lends itself well to the analysis of data for inferential purpose. By contrast, most other multivariate procedures are essentially descriptive by nature, so that hypothesis testing is difficult, if not impossible. Second, although traditional multivariate procedures are incapable of either assessing or correcting for measurement error, SEM provides explicit estimates of these error variance parameters (Byrne, 2009). All the statistical analyses were conducted using the Amos 4.0 software.

Table 1 show the variety of different fit indices used in structural equations modeling. To clarify things, stringent thresholds levels are inventoried in a column and Acceptable threshold levels for complex models in a second column. In the field of structural equation modeling, it is difficult to have stringent thresholds (Kenny and McCoach, 2003; Marsh *et al*., 2004) this is why many authors (Table 1) gave the solution by acceptable threshold levels.

Tunisian soil organic stocks and their maps: For Tunisia, organic stocks were already calculated in previous studies. In fact, the TN stock (Ibrahim *et al*., 2009) and the OC stock (Brahim *et al*., 2011a) were calculated from 0-30 cm depth and maps of density were developed in this topic (Fig. 2). The methodology used by these authors is summarized as follows:

Soil map: The soil map constructed by Belkhodja *et al*. (1973) at the scale (1:500.000) is digitized. Nine main orders of soils were inventoried: Lithosols, Regosols, Cambisols, Vertisols, Kastanozems, Podzoluvisools, Luvisols, Solonchaks and Gleysols. The total number of soil map units was 34049.

Procedure for determining the individual SOC stocks and TN stocks: To estimate SOC or TN stocks, requires knowledge of the vertical distribution of OC in profiles. The way of calculating stocks for a given depth consists of summing SOC Stocks by layer determined as a product of D_b, OC concentration and layer thickness. For an individual profile with n layers, we estimated the organic carbon stock by the following equation:

$$\text{Stock} = \sum_{i=1}^{n}[D_{bi} \times (\text{OC } or \text{ TN})_i \times D_i]$$

where, Stock is expressed in kg OC or TN/m^2, D_{bi} is the bulk density (Mg/m^3) of layer i, OCi or TNi is the proportion of organic carbon (g OC/g) and total nitrogen (g TN/g) in layer i, respectively. Di is the thickness of this layer (cm). Next step of calculation, SOC density or TN density of each great order was multiplied by its respective area to estimate SOC storage for each soil map units. Summation of individually of carbon of the nine great soil orders gave total carbon and nitrogen stock in Tunisia.

RESULTS AND DISCUSSION

The database of Tunisian soils: This study used data from the Tunisian soils. For building of two models of TN stocks under clayey soils and sandy soils, two databases were used. The first was constructed from clayey soils, it was made of 170 soil profiles, corresponding to 450 soil horizons, the second was constructed from sandy soils it was made of 602 soil horizons, corresponding to 285 soil profiles. Descriptive statistics for all databases are reported in Table 2.

Pedotransfer Functions (PTFs) for estimating TN stocks:

PTFs for clayey soils: Multiple Linear Regression (MLR) analyses were carried out on all the data and subgroups according to soil types.

In the linear regressions, only parameters with statistical significance at the 0.01 significance level were considered for computing predictive equations and reporting results. Standard Error of the estimate (SE) and percentage of variance explained, through R values, were used as means to evaluate the reliability of the models. The input variables were chosen either because they are known to influence TN stocks.

In order to group the different soil properties to the smallest possible subsets representing most of the original data set variation, PCA was performed and then these variables were summarized into four principal components with eigenvalue >1, interpreting 68.47% of the total variance (Table 3).

The first and the most important component (PC1), explaining 22.65% of the variation, showed high factor loadings (>0.50) for OC, OM, D_b and soil pH. The second component (PC2) loaded heavily on coarse silt and fine sand and explained 18.86% of the total variance. The third component (PC3) had high loadings for soil clay, fine silt contents, OC/TN and $CaCO_3$. The highly weighted variables in the fourth component (PC4) were coarse sand.

Table 4 shows the matrix of correlations between TN stock and soil properties. There are 13 variables in the matrix. The correlation coefficients show that a TN stock is significantly related to 5 variables (F-Silt, C-Silt, F-Sand, TN and OC/TN) at the 0.05 probability level.

Relationships of TN stock with soil properties were obtained by multiple regression analysis with the

Table 2: Summary of indicative thresholds adjustment tests of SEM

	Clay	F-silt	C-silt	F-sand	C-sand	OC	pH	OM	D_b	$CaCO_3$	TN	OC/TN	TN stock t/ha 0-30 cm depth
Database of clayey soils													
Valid case	450	450	450	450	450	450	450	450	450	450	450	450	450
Minimum	18.00	0.00	0.00	0.00	0.00	0.10	5.40	0.11	0.87	0.00	0.01	1.40	0.139
Maximum	81.40	51.00	30.10	30.60	38.00	6.40	9.62	11.00	1.80	85.80	2.79	75.00	179.28
Mean	45.77	22.84	12.18	12.25	7.32	1.19	7.90	2.05	1.50	15.09	0.24	11.81	8.80
Std. deviation	12.33	9.87	7.17	7.16	6.91	0.92	0.66	1.63	0.14	17.10	0.45	6.03	19.11
Variance	151.91	97.39	51.41	51.29	47.78	0.86	0.44	2.65	0.02	292.55	0.20	36.37	365.07
Database of sandy soils													
Valid case	602	602	602	602	602	602	602	602	602	602	602	602	602
Minimum	0.00	0.00	0.00	0.00	0.10	0.06	4.90	0.01	0.63	0.00	0.00	0.00	0.10
Maximum	41.00	49.00	47.00	84.00	93.00	5.78	9.30	11.00	1.90	98.21	1.72	58.52	84.00
Mean	16.56	16.27	10.54	29.87	29.83	1.03	7.46	1.90	1.57	11.11	0.13	3.93	10.97
Std. deviation	8.62	11.39	6.82	14.98	20.71	0.95	1.01	1.75	0.15	13.46	0.19	5.79	6.86
Variance	74.22	129.78	46.51	224.41	428.75	0.90	1.02	3.06	0.02	181.15	0.03	33.55	47.10

Table 3: PCA results based on different clayey and sandy soil properties

Database	Clayey soils				Sandy soils				
Principal component	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC5
Eigenvalue	3.08	2.26	1.70	1.18	2.843	2.10	1.44	1.29	1.05
% total variance	25.65	18.86	14.15	9.80	23.69	17.54	11.96	10.74	8.77
Cumulative %	25.65	44.52	58.67	68.47	23.69	41.23	53.20	63.94	72.71
Factor loading									
Clay	0.45	-0.33	-0.54	0.40	0.04	0.61	-0.60	0.12	0.03
F-silt	-0.29	-0.26	0.67	0.29	0.02	0.46	0.13	0.34	-0.04
C-silt	-0.42	0.87	0.00	-0.02	0.02	0.66	-0.04	-0.27	-0.02
F-sand	-0.43	0.87	0.00	-0.03	-0.09	0.27	0.88	0.00	-0.04
C-sand	0.25	-0.18	-0.05	-0.90	-0.03	-0.92	-0.30	-0.02	0.00
OC	0.85	0.31	0.29	0.09	-0.19	-0.13	0.13	0.75	0.03
pH	-0.52	-0.33	0.09	0.20	0.93	0.06	-0.01	-0.09	-0.03
OM	0.85	0.32	0.30	0.09	0.93	0.09	-0.01	-0.10	-0.01
D_b	-0.78	-0.11	-0.04	-0.07	-0.66	0.16	0.49	0.19	0.06
TN	0.20	0.45	-0.28	0.16	0.35	0.10	-0.06	-0.11	-0.75
OC/TN	-0.06	0.03	0.59	0.08	0.19	0.04	-0.08	-0.08	0.86
$CaCO_3$	0.08	-0.11	0.59	-0.17	-0.09	0.06	-0.16	0.80	-0.01

Table 4: Bivariate correlation of TN stock with some clayey soil properties

	TN stock	Clay	F-silt	C-silt	F-sand	C-sand	$CaCO_3$	D_b	pH	OM	OC	TN	OC/TN
TN stock	1.000												
Clay	-0.027	1.000											
F-silt	-0.140**	-0.426**	1.000										
C-silt	0.233**	-0.415**	-0.154**	1.000									
F-sand	0.221**	-0.416**	-0.156**	0.974**	1.000								
C-sand	-0.034	-0.144**	-0.277**	-0.243**	-0.243**	1.000							
$CaCO_3$	-0.065	-0.125**	0.204**	-0.075	-0.076	0.099*	1.000						
D_b	0.011	-0.287**	0.196**	0.195**	0.218**	-0.133**	-0.050	1.000					
pH	-0.037	-0.059	0.232**	-0.029	-0.029	-0.122**	0.098*	0.321**	1.000				
OM	0.030	0.135**	-0.094*	-0.083*	-0.085*	0.077	0.150**	-0.599**	-0.424**	1.000			
OC	0.026	0.143**	-0.098*	-0.097*	-0.098*	0.084*	0.134**	-0.596**	-0.420**	0.993**	1.000		
TN	0.835**	0.049**	-0.166**	0.213**	0.193**	-0.041	-0.092*	-0.202**	-0.088*	0.194**	0.193**	1.000	
OC/TN	-0.195**	-0.167**	0.178**	0.058	0.061	-0.065	0.157**	-0.041	0.086*	0.064	0.074	-0.195**	1.000

**: Correlation is significant at the 0.01 level; *: Correlation is significant at the 0.05 level

Table 5: Bivariate correlation of TN stock with some sandy soil properties

	TN stock	clay	F-silt	C-silt	F-sand	C-sand	$CaCO_3$	D_b	pH	OM	OC	TN	OC/TN
TN stock	1.000												
Clay	0.061	1.000											
F-silt	0.019	0.123**	1.000										
C-silt	0.099*	0.150**	0.065	1.000									
F-sand	-0.032	-0.266**	0.138**	0.012	1.000								
C-sand	-0.039	-0.430**	-0.382**	-0.520	-0.552**	1.000							
$CaCO_3$	-0.005	0.129**	0.113**	-0.082**	-0.063	-0.034	1.000						
D_b	-0.071	-0.145**	0.067	0.057*	0.450**	-0.237**	0.126**	1.000					
pH	-0.024	-0.047	0.070	-0.106**	0.031	0.083*	0.369**	0.348**	1.000				
OM	0.109**	0.111**	-0.035	0.138**	-0.107**	-0.102*	-0.168**	-0.530**	-0.239**	1.000			
OC	0.094*	0.094*	-0.062	0.120**	-0.104*	-0.076	-0.162**	-0.552**	-0.228**	0.863**	1.000		
TN	0.764**	0.057	0.011	0.123**	-0.013	-0.068	-0.088*	-0.290**	-0.148**	0.312**	0.284**	1.000	
OC/TN	-0.318**	0.063	-0.037	0.040	-0.093*	0.001	-0.046	-0.128**	-0.061	0.122**	0.083*	-0.315**	1.000

**: Correlation is significant at the 0.01 level; *: Correlation is significant at the 0.05 level

stepwise method using the PCA-derived subset of al variables using all the available parameters, the best MLR resulted in the following equation is:

$$\text{TN stock} = 6.494\ (\pm 2.854) + 0.577\ \text{C-Silt}\ (\pm 0.123) - 0.207\ \text{F-Silt}\ (\pm 0.09)$$
$$(R = 0.256;\ SE = 18.51;\ p = 0.000 < 0.05)$$

The regression equation were highly significant ($p = 0.000$) and relationships is given essentially by the two variables coarse silt and fine silt. Therefore we find that the stock of total nitrogen is explained by the physical properties (coarse and fine silt) and not by chemical properties.

PTFs for sandy soils: We proceed in the same way as clay soils. PCA was performed and then these variables were summarized into five principal components with eigenvalue >1, interpreting 72.71% of the total variance (Table 3).

The first component (PC1), explaining 23.69% of the variation, showed high factor loadings (>0.50) for soil pH, OM and D_b. The second component (PC2) loaded heavily on coarse sand, coarse silt and clay and explained 17.54% of the total variance. The third component (PC3) had high loadings for fine sand and clay contents. The fourth component (PC4) had high factor loadings for $CaCO_3$ (0.80) and OC (0.75). The highly weighted variables in the fifth component (PC5) were TN and OC/TN.

Table 5 shows the matrix of correlations between TN stock and soil properties. There are 13 variables in the matrix. The correlation coefficients show that a TN stock at sandy soils is significantly related to 5 variables, where OM, TN and OC/TN at the 0.01 level of significance; and Coarse silt and OC at the 0.05 probability level.

Using all the available parameters, the best MLR resulted in the following equation:

$$\text{TN stock} = 3.044\ (\pm 0.433) + 0.84\ \text{C-Silt}\ (\pm 0.035)$$
$$(R = 0.099;\ SE = 5.76;\ p = 0.016 < 0.05)$$

Pedotransfer function is significant at $p = 0.016$ (<0.05*) and relationships is given by the only coarse silt variable. Same with sandy soils, we come across the same result; the TN stock is explained first by the physical properties (coarse silt).

R is relatively low for both PTF equations. However, they are reliable by significant p and statistically are acceptable. We searched for PTF with physical properties (Clay, silt and sand) for two reasons:

- When the nitrogen content was then the stock is estimated directly
- We have tried to determine the variable that controls the storage in such type's soils under arid and semi-arid zones

Modeling TN stocks by SEM:

SEM for clayey soils: Statistical modeling is an accepted scientific practice. In this study, we use the Structural Equation Modeling (SEM), this methodology is characterized by:

- Translation of the soil rather complicated phenomena and to express it in terms of environmental conceptual factors.
- Consolidation, after exploratory factor analysis (EFA, exploratory factor analysis: EFA), factors measured in question with the observed variables assuming explicitly that alone cannot explain the latent variable.

We followed the following methodology:

- Firstly, through an exploratory factor analysis (or PCA), we created a conceptual model explaining the organic carbon content in this stage, we use the statistical software SPSS 16.0.
- Then, after determining the latent structure, we conducted a Confirmatory Factor Analysis (CFA), at this level, we test statistically the relationships between variables using the software Amos 4.0. Using this method, our model provided more accurate estimates due to estimation error term. The steps in the structural equation modeling are well detailed by Brahim *et al*. (2011b). After carrying out the different steps, we built the model of nitrogen stocks in the clayey soils of Tunisia. The model is focused on Fig. 3. We found that the TN stock is determined by two variables. The first latent variable "Physical properties" with three indicator variables, Clay, C-Silt and F-Sand. The second latent variable "Chemical properties and D_b" is measured by three observed variables, OM, pH and D_b. The principle of the selection of these indicators is based on the results of Principal Component Analysis (PCA). Figure 3 shows the covariance between measurement errors for the observable indicators of latent exogenous variables (δ1 and δ6), bulk density (D_b) is generally associated with clay (Jones, 1983; Bernoux *et al*., 1998; Benites *et al*., 2007). The model has a value of χ^2 = 2 46 742 (Degree of Freedom DF = 12) and the value χ^2/DF = 3.89 (<5) is satisfactory according to James *et al*. (1982).

From the RMR value of 3.217, we can conclude that this model is acceptable. According to the and AGFI whose values 0.972 and 0.936 respectively, we can conclude that our model is also satisfactory. In the case of this model value is 0.417 PGFI this index takes into account the complexity of the model (Mulaik *et al*., 1989). Generally, the index of parsimony is accepted for a lower threshold than that of adjustment index. In our case the PGFI is also acceptable because of this low value. With regard to the index CFI it provides a comprehensive measure of covariance in the data and the value 0.980 for a model was considered representative (Bentler, 1989) suggesting that the model represents an appropriate form of data. Finally, the RMSEA takes into account the error of approximation. It is independent of the sample size of the database and the complexity of the model (Browne and Cudeck, 1989, 1993). Values less than 0.080 indicate a good model fit.

SEM for sandy soils: We performed the same way for modeling TN stock in sandy soils than TN stock modeling in clay soils. The resulting model is focused on Fig. 4. Latent variables in sandy soils are "chemical properties and D_b" and "physical properties". These two latent variables are related to the observed variables.

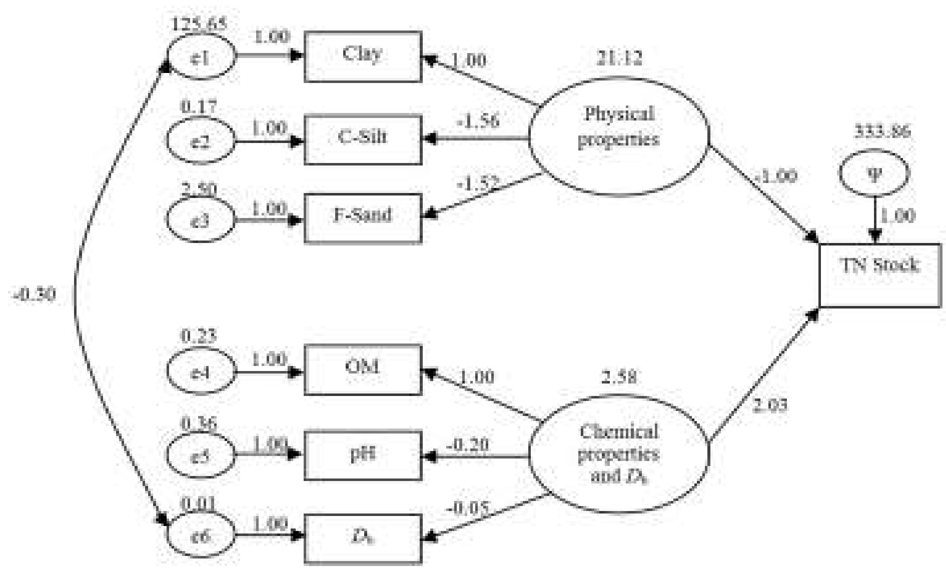

Fig. 3: The estimated parameters of the model predicting TN stock in Tunisian clayey soils
χ^2 (chi-square) = 46.742; DF (Degrees of Freedom) = 12; GFI (Goodness of Fit Index) = 0.972; AGFI (Adjusted Goodness of Fit Index) = 0.936; RMR (Root Mean Square Residual) = 3.217; NFI (Normed Fit Index) = 0.974; PGFI (Parsimony Goodness of Fit Index) = 0.417; RFI (Relative Fit Index) = 0.954; IFI (Incremental Fit Index) = 0.980; TLI (Bentler-Bonett non-normed fit index or NNFI) = 0.966; CFI (Comparative Fit Index) = 0.980; RMSEA (Root Mean Square Error of Approximation) = 0.080

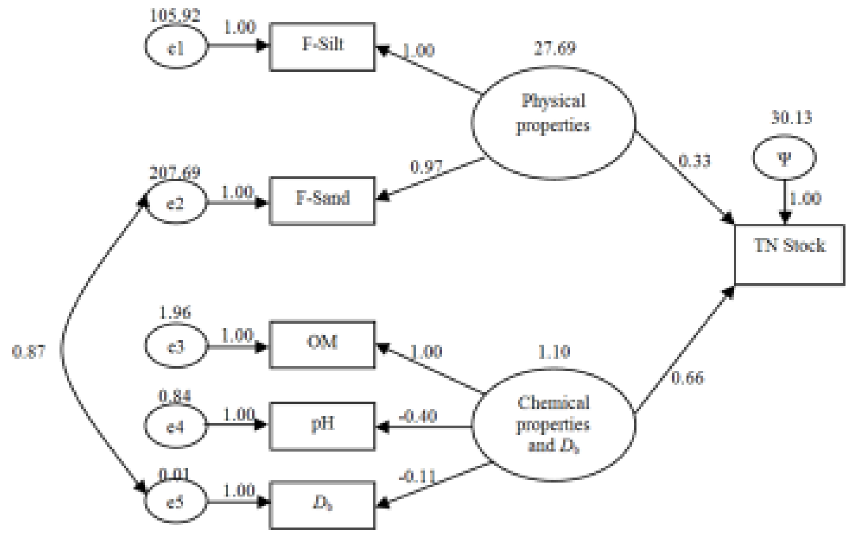

Fig. 4: The estimated parameters of the model predicting TN stock in Tunisian sandy soils
χ^2 = 14.727; DF = 7; GFI = 0.992; AGFI = 0.976; RMR = 1.207; NFI = 0.970; PGFI = 0.331; RFI = 0.935; IFI = 0.984; TLI = 0.965; CFI = 0.984; RMSEA = 0.043

We have assumed that the first latent variable "physical properties" as an indicator variables measured, the F-Silt and F-Sand. The second latent variable is measured by two variables observable pH, OM and D_b.

The principle of selection of these indicators is based on the findings of the analysis by PCA. Because naturally the bulk density (D_b) is associated with the mineral fraction of the soil (Jones, 1983; Bernoux *et al*., 1998; Benites *et al*., 2007), we show the covariance between measures errors for the observed indicators of exogenous latent variables (δ2 and δ5).

The model has a value of χ^2 = 14.724 (degree of freedom df = 7) and the value χ^2/df = 2.10 (<5) is satisfactory according to James *et al*. (1982). From RMR of 1.207; we can conclude that this model is acceptable. From the values of GFI = 0.992 and AGFI = 0.976, we can conclude that the model is also satisfactory. PGFI value of 0.331 is significant according to Mulaik *et al*. (1989). Relative Fit Index and Incremental Fit Index (0.935 and 0.984) are representative values and the model is acceptable. The CFI and TLI values which are 0.984 and 0.965, respectively suggest that the model represent an appropriate form of data.

The RMSEA takes into account the error of approximation. It is independent of the sample size and the complexity of the model. According to Browne and Cudeck (1989, 1993) values below 0.08 indicate a good fit of the model, in this model RMSEA = 0.043.

Comparison of the two types of models (PTFs and SEM): After modeling the stock of total nitrogen in clayey and sandy soils of Tunisia by two methods, with Pedotransfer Functions (PTFs) and with the structural equations, we conclude that the PTFs do not take into account all the variables of the soil and in both soil types we obtained models with "physical properties" that are coarse and fine silt for clayey soils and coarse silt for sandy soils. Although the models are significant (p<0.05) they have low R values. However, they show that silt is a fraction in the intercalation of essential stock of total nitrogen in different Tunisian soils.

For Structural Equations Modeling (SEM), we tested the interaction of different physicochemical variables at the same time, we understand that, in addition to the silt fraction, which is essential in the storage already determined by PTFs, other variables can control the stock. Using SEM, we have built and tested two models, which provides an adequate explanation for the change in the stock of total nitrogen in two types of soil: clayey and sandy.

The results show that in clayey soils, the chemical and bulk density properties play the most important role in the control of the stock of total nitrogen. In fact, pH, OM and D_b are the main variables responsible for the storage of total nitrogen with γ (coefficients of exogenous latent variables) = 2.03 against γ = -1.00 for physical properties (clay, coarse silt and fine sand). The same result is obtained with sandy soils, where the results show that the chemical and bulk density properties (pH, OM and D_b) with γ = 0.66 are the best indicators of the stock of total nitrogen as factors physical with γ = 0.33.

The soils of arid and semi-arid Mediterranean area are threatened by erosion and desertification and the recovery of these degraded lands requires sequestration of organic matter and total nitrogen among other inhibits both phenomena and improves fertility soil. Both models illustrate the main factors affecting the organic stock in the clayey and sandy soils.

With both types of models (PTF's and SEM) are founded at the level of the Tunisian aridisols, TN is related to the fine particles of the soil, primarily to the silt. These results are in corroboration with its several soil studies in temperate and tropical zones. The stabilization of OC and TN by association with silt and clay particles has been investigated in many studies. Several studies reported a relationship between clay or silt plus clay content and the preservation of OC and TN (Feller and Beare, 1997; Hassink, 1997). It has also been reported that not only the clay content but also the clay type influences the preservation of OC and TN (Ladd *et al*., 1992; Torn *et al*., 1997; Sorensen, 1971). Feller *et al*. (1996) linked critical values of soil organic matter for both soil fertility and erodibility in tropical soils. A critical threshold of soil organic matter, based on a linear equation utilizing soil silt and clay content, was useful in predicting the sustained fertility and productivity of a collection of tropical soils (Feller and Beare, 1997). Six *et al*. (2002) regressed the amount of OC associated with silt and clay content (%) for tropical and temperate soils and both regression lines were significant, indicating a positive influence of clay and silt particles on OC stabilization. However, the coefficient of determination was lower in temperate than in tropical soils. Results also indicate a lower stabilization of OC per unit of silt and clay particles and, hence, a lower OC protective capacity of the silt and clay particles in tropical versus temperate soils.

CONCLUSION

The current study shows that changes in the stock of total nitrogen with soil texture are positively correlated with the chemical and physical properties of the soil.

After performing a Principal Components Analysis (PCA) and pedotransfer equations (PTFs) it was found that the physical properties of soils can explain better storage than chemical properties. And this result is validated in two soil types (clayey and sandy).

With the Structural Equation Modeling (SEM), two models were constructed. These models have provided a satisfactory explanation of the variance of the stock of total nitrogen in two different soil types (clayey and sandy).

The results show that the physical and chemical properties have independent effects on the stock. Indeed, the results show that in clay soils, chemical properties and bulk density are the most important role in controlling the stock of nitrogen. Organic matter, pH and D_b are the main variables responsible for the storage of OC linked to? Physical properties which are clay, coarse silt and fine sand. Similarly, in sandy soils results show that chemical factors (i.e., OM, pH and D_b) are the best indicators of the TN stock that the physical properties (fine silt and fine sand).

We can build relationships with simple PTFs to explain the stock of nitrogen in two soils when we have a small number of variables, although the SEM is the best in the explanation because of complexity with all variables. Results also suggest that SEM models explain better the total nitrogen stock than PTFs models.

Soils at semi-arid Mediterranean climate are specially threaten by erosion and desertification phenomena and the restoration of these soils needs a carbon and nitrogen sequestration which inhibit these two phenomena and enhance soils fertility.

Both models illustrate the key factors influencing the nitrogen storage in clay and sandy soils. Finally, the two models could be generalized in all arid and semi-arid Mediterranean area.

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