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Prediction of soil total nitrogen based on total organic carbon using different models in soils from the Iraqi Kurdistan Region.

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ABSTRACT

Determining the total nitrogen in the soil in a lab takes a long time and requires a lot of different chemicals; this method could be faster and cheaper. Therefore, using pedotransfer to predict total nitrogen (TN) in soil based on soil organic carbon (SOC) is more convenient and economical. Using five equations, including exponential, linear, logarithmic, polynomial, and power models, to predict TN from SOC. The results showed that TN could be predicted as a function of SOC, and the Bland-Altman approach was used to compare the predicted soil TN with the measured TN in the lab. The mean difference between the two approaches at 95% limits of agreement between field and lab measurements of soil TN was 0.000 g kg $^{-1}$. The calculated values for the soil TN pedotransfer function were - 0.350 and + 0.350 g kg $^{-1}$. The polynomial model (TN = - 0.667 + 0.203 x OC - 0.004 * OC ^{2}) and linear model (TN = - 0.263 + 0.124*OC) equations were considered the best model for predicting soil total nitrogen of studied soils due to their high R^2 (0.820, and 0.814) and low RMSE (0.183, and 0.184).

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Keywords: Polynomial Model, Total Nitrogen, Soil Organic Carbon, Prediction.

1. Introduction

Nitrogen is a primary plant element and is frequently the limiting nutrient in crop production. Organic matter, which is mainly made up of nitrogen (N), phosphorus (P), and sulfur (S), is one of the most important sources of nutrients for plants. Nitrogen is an essential nutrient for plants, and sufficient nitrogen fertilizer application is essential for maximum plant growth and development. Nitrogen is a significant component of chlorophyll and, therefore, is necessary for photosynthesis and crop protein synthesis (Vitousek, 1982; Vitousek et al., 1997). Chen et al. (2018) and Otto (2016) demonstrate that the soil's total nitrogen significantly influences plant growth. As a result, it is essential to evaluate the amount of total nitrogen in the soil to increase crop production and farmers' income. Soil organic carbon is important to soil function, soil quality management, plant nutrition availability, and soil water holding capacity (Flessa et al., 2000). Odell et al. (1984) reported that sustainable agricultural production could be attained by increasing organic carbon and soil total nitrogen or maintaining these levels close to their native levels. "Pedotransfer function" (PTF) is used in soil science to describe functions that can predict certain soil qualities based on other properties that are easier to measure, more common, or less expensive. Generally, a "pedotransfer function" (PTF) turns simple soil data into more helpful information. It may also predict characteristics of soil that are difficult to determine from basic, often-measured, or cheaply-measured values. The PTFs add value to the original soil data by transforming the primary soil data into predictors of other soil variables that require more time and money. These functions fill the gap between existing soil data and other characteristics that are more important or necessary for a specific model or quality evaluation (Van Looy et al., 2017). Spectroscopic methods are frequently used to evaluate crop production because they are fast, inexpensive, and harmless to the crops (Liu, 2017; Kwan, 2018; Iqbal, 2014). When studying the carbon and nitrogen cycles, it is often necessary to measure the carbon and nitrogen levels of the soil many times. When normal analytical methods are used, this takes time and costs money. Near-infrared reflectance (NIR) spectroscopy is getting more attention because it can quickly and cheaply measure soil qualities, especially the amount of total carbon (Ct) and nitrogen (Nt) in the soil (Barthès et al., 2006). St. Luce et al. (2012) demonstrated that accurate near-reflectance spectroscopy (NIRS) models could be developed to predict soil total N and organic C concentrations and the C/N ratio across agricultural soils in Canada's humid region. In addition, NIRS can be used to test soil quickly, accurately, and cheaply, it could replace some of Canada's older methods that are done in the lab. Visible and near-infrared (VIS-NIR) spectroscopy can measure soil parameters like total nitrogen, organic carbon, and moisture content because

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these variables have direct spectral interactions in the near-infrared (NIR) region. Morellos et al. (2016) show that machine learning methods can solve non-linear problems in datasets. Linear multivariate methods were not as good at predicting the three soil properties as LS-SVMs and the cubist technique. Root mean square error of prediction (RMSEP) = 0.457%, residual prediction deviation (RPD) = 2.24, and OC (RMSEP = 0.062%, RPD = 2.20) was best predicted using LS-SVM, whereas the best prediction for TN (RMSEP = 0.071%, RPD = 1.96) was achieved with the Cubist Method. Traditional modeling methods frequently require complex data preprocessing to determine soil total nitrogen content because there is no nonlinear relationship between soil total nitrogen and soil spectra. Principal component regression and partial least squares are typical modeling methods for quantitative soil spectroscopy (Kooistra et al., 2001; Vasques et al., 2008). With sufficient training data from various soil types and countries, the convolutional neural network deep learning technique used to model soil total nitrogen content provides strong generalization. Since it applies to all different kinds of soil and countries, it can be used as a standard. In that case, the best alternative is a machine capable of extraordinary learning (Wang et al., 2020). This study used the amount of organic carbon in the soil to determine the total amount of nitrogen in the soil based on the amount of organic carbon, a pedotransfer function was proposed to predict the total amount of nitrogen in the soil. No studies in our area use total soil organic carbon to predict total soil nitrogen. As a result, the specific objective of this research is to:

- Predict the TN of the studied soils using the best models based on soil organic carbon.

- To validate the constructed model, compare its results to the findings of laboratory experiments.

2. Methods and Materials

Soil databases were taken from the University of Sulaimani, Natural Resource Department, College of Agricultural Engineering Sciences. This database consisted of data from 41 years (1979–2020). One hundred thirty soil samples, ranging in depth from 0 to 30 centimeters, were taken from several areas in the Iraqi Kurdistan region. Some of the soil physiochemical characteristics used in this study were particle size distribution(PSD), soil organic carbon, and total soil nitrogen. Some of the physiochemical properties of the soil studied include particle size distribution determined by sieving and pipette methods and total soil nitrogen determined using the procedure outlined by Estefan et al. for soil, plant, and water analysis (2013). Nelson and Sommers (1983) determined oxidizable organic matter using the Walkley and Black moist dichromate oxidation method. They also validated the total soil nitrogen-organic carbon models using laboratory studies. Forty-five soil samples were randomly chosen from various locations to test the total soil nitrogen-organic carbon model. Table 1 shows the physiochemical characteristics of the 45 samples that tested the soil TN - OC model. Table 2 shows five mathematical models for predicting TN from soil organic carbon, including exponential, linear, logarithmic, polynomial, and power models. The best model equation was revealed to have the highest determination coefficient (R^2) and the lowest root mean square error (RMSE). The following formulas were used to calculate the root mean square error (RMSE) and determination coefficient (R^2):

1. $\text{RMSE} = \frac{\sqrt{\sum_{i=0}^{n} (O_i - P_i)^2}}{n}$

Where:
RMSE = root mean square error, Oi = observed values,
Pi = predicted values,
n = number of observations

2. $R^2 = 1 - \frac{\sum(yi - \hat{y})^2}{\sum(yi - \bar{y})^2}$

Where:
R^2 = Determination coefficient, y_i = observed value of y
$\hat{y}$ = predicted value of y

Table 1: The soil TN - SOC model was validated in the studied region using statistical results of physiochemical from 45 soil samples.

Parameters g kg $^{-1}$	**Minimum**	**Maximum**	**Mean**	**S.D.**	**C.V. (%)**
Sand	34.000	276.100	121.700	66.290	54.470
Silt	274.000	761.000	451.102	108.214	23.989
Clay	104.400	692.000	427.199	124.935	29.245
Soil organic carbon	5.452	17.013	10.763	3.060	28.428
Total nitrogen	0.330	1.970	1.075	0.421	39.201

Table 2: Various models were used in the studied soils.

Models	Equations	Parameters
Exponential	$\hat{Y} = a\, e^{bX}$	$\hat{Y}$ = Dependent variable (soil total nitrogen) X = Independent variable (soil organic carbon) e = Base of the natural logarithm, 2.718 a, b = Regression coefficients
Linear	$\hat{Y} = a + bX$	$\hat{Y}$ = Dependent variable (soil total nitrogen) X = Independent variable (soil organic carbon) a = intercept b = slope

Logarithmic	$\hat{Y} = a + b \ln(X)$	$\hat{Y}$ = Dependent variable (soil total nitrogen) X = Independent variable (soil organic carbon) Ln = Logarithms to the base e (called natural logarithms) a = intercept b = slope
Polynomial (Quadratic)	$\hat{Y} = a + b X + cX^2$	$\hat{Y}$ = Dependent variable (soil total nitrogen) X = Independent variable (soil organic carbon) a = intercept b, c = slope
Power	$\hat{Y} = a X^b$	$\hat{Y}$ = Dependent variable (soil total nitrogen) X = Independent variable (soil organic carbon) a, b = Regression coefficients

Statistical analysis

The XLSTAT software program was performed descriptive analyses like average, minimum, maximum, standard deviation, and coefficient of variance (Addinosoft, 2016). The consistency between the laboratory-determined soil TN values and the predicted soil total nitrogen values obtained from the total soil nitrogen-soil organic carbon model was plotted using the Bland-Altman technique (1999).

3. Results and Discussion

Soil total nitrogen was predicted using five models based on soil organic carbon, including exponential, linear, logarithmic, polynomial, and power. Model equations were ranked according to their R^2 and RMSE values; The best model equation had a high R^2 and a low RMSE. In this study showed that the polynomial model (TN = - 0.667 + 0.203 x OC - 0.004 * OC^2) and the linear model (TN = - 0.263+0.124* OC) equations were considered the best models for predicting total soil nitrogen of studied soils due to their high R^2 (0.820 and 0.814) and low RMSE (0.183 and 0.184), as shown in (Table 3). Rashidi and Seilsepour (2009) showed that the best predictor of soil total nitrogen for calcareous soils in the Varamin region of Iran was a linear pedotransfer function (TN = 0.026 + 0.067 OC) utilizing soil organic carbon. Musa et al. (2016) concluded that a linear regression model (TN-SOM model) with the equation TN% = 0.04 x OM + 0.05 and R^2 = 0.604 is suitable for predicting total soil nitrogen from soil organic matter in 15 soil samples collected from the experimental area (Wadi Soba farm, Khartoum- Sudan). In fields with a high clay content, however, Kuang and Mouazen (2013) recommend taking TN and OC readings online and in the lab under dry soil circumstances by using validation datasets from the two research locations. Alshujairy and Ali (2017) showed that visible near-infrared radiation (VNIR)-based and GIS-Kriging models can be used to identify new soil samples. Rumetha's Q^2 between predicted total N values and laboratory-measured total N values was 0.28, whereas Samawa's Q^2 was 0.43, indicating that GIS-Kriging models were not adequately cross-validated. While VNIR-based validation models demonstrated strong predictive power, with an R^2v of 0.84 between laboratory-measured and predicted total N values in Rumetha and 0.85 in Samawa.

Table 3: Predictions of soil TN have been calculated using the coefficient of determination (R^2) and root-mean-square error (RMSE) of five models based on soil organic carbon.

Models	RMSE	R^2
Exponential	0.205	0.770
Linear	0.184	0.814
logarithmic	0.187	0.809
Polynomial	0.183	0.820
Power	0.428	0.016

A graphical tool that can be used to compare two different measuring techniques is the Bland-Altman plot (1999), also known as the difference plot. It compares soil TN measured in the lab to soil TN predicted by the pedotransfer function. Table 4 shows laboratory TN values for soil and pedotransfer function predictions for TN values in soil. Figure 1 shows a plot of the soil TN values obtained from laboratory tests and the soil TN pedotransfer function using the line of equality (1.0:1.0). Comparing the laboratory values of soil TN to the pedotransfer function for soil TN, 95% confidence intervals ranged from - 0.350 g kg^{-1} to + 0.350 g kg^{-1}. The average soil TN value measured by the two techniques was the same (0.000 g kg^{-1}) (Fig. 2). The soil TN pedotransfer function may predict a value for soil TN that is either - 0.350 g kg^{-1} lower than or + 0.350 g kg^{-1} higher than the value obtained by laboratory analysis. Table 4 also shows that soil OC varied from 5.452 to 17.013 g kg^{-1} for all forty-five samples. Statistics also show that the predicted soil TN from the soil TN pedotransfer function is very close to the soil TN measured in a laboratory.

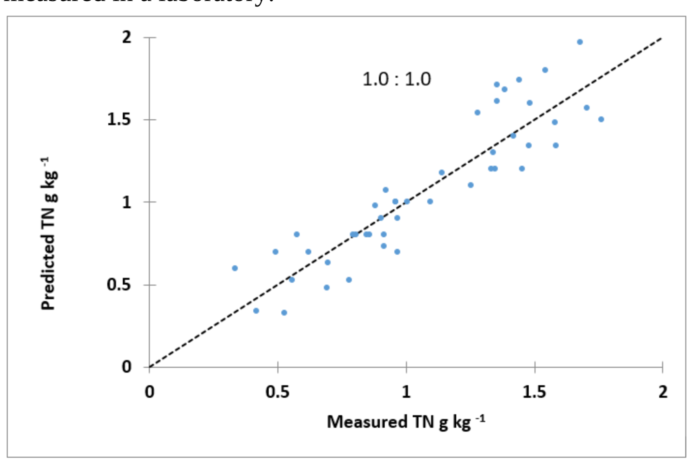

Figure 1: Measured and predicted soil total nitrogen using the line of equality model for soil total nitrogen and soil organic carbon (1.0:1.0).

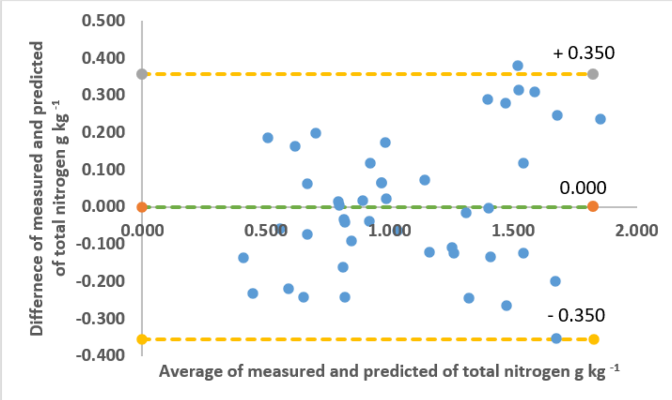

Figure 2: The outer lines represent the 95% limits of agreement (-0.350, + 0.350) for the soil TN - OC model, and the measured and predicted TN values are represented by the outside and inside lines, respectively, by the central line (- 0.000).

Table 4: The soil TN - OC model is evaluated based on the chemical characteristics of soil samples.

Sample No.	Soil organic carbon g kg $^{-1}$	Soil total nitrogen g kg $^{-1}$	
		Laboratory test (measured value)	Soil TN-OC model (predicted value)
1	9.977	1.000	1.006
2	13.747	1.200	1.454
3	9.281	0.800	0.912
4	8.875	0.800	0.856
5	7.773	0.630	0.697
6	12.761	1.200	1.347
7	6.845	0.530	0.557
8	11.949	1.100	1.253
9	9.629	1.000	0.959
10	9.281	0.730	0.912
11	9.049	0.980	0.880
12	8.817	0.800	0.848
13	5.452	0.600	0.335
14	13.979	1.340	1.478
15	16.357	1.570	1.705
16	9.339	1.070	0.920
17	9.687	0.700	0.967
18	16.067	1.970	1.679
19	12.181	1.540	1.280
20	12.819	1.710	1.353
21	14.617	1.800	1.543
22	13.631	1.740	1.442
23	15.023	1.340	1.583
24	5.945	0.340	0.415
25	7.744	0.480	0.693
26	8.324	0.530	0.778
27	15.017	1.480	1.582
28	6.647	0.330	0.526
29	6.961	0.800	0.575
30	8.511	0.800	0.804
31	9.210	0.900	0.902
32	8.443	0.800	0.795
33	6.429	0.700	0.492
34	9.671	0.900	0.965
35	10.666	1.000	1.095
36	17.013	1.500	1.760
37	12.825	1.610	1.354
38	13.109	1.680	1.385
39	11.021	1.180	1.140
40	14.037	1.600	1.484
41	13.399	1.400	1.417
42	12.645	1.200	1.333
43	12.703	1.300	1.340
44	7.251	0.700	0.619
45	9.629	1.000	0.959

Conclusion

The polynomial model (TN = - 0.667 + 0.203 x OC - 0.004 *OC^2) and linear model (TN = - 0.263 + 0.124*OC) were the best models to predict the total nitrogen in the studied soils due to their high R^2 (0.820, and 0.814) and low RMSE (0.183, and 0.184). The TN content of the soil did not differ significantly between the two methods (0.000 g kg $^{-1}$). The total soil nitrogen predicted by the pedotransfer function may vary from the total soil nitrogen measured in a laboratory by - 0.350 g kg $^{-1}$ or + 0.350 g kg $^{-1}$. The amount of organic carbon in the 45 samples varied from 5.452 g kg $^{-1}$ to 17.013 g kg $^{-1}$. The pedotransfer function predicts nearly the same amount of total nitrogen in the soil.

Conflict of interests

The author claims no conflict of interest.

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Author contribution

The author wrote, reviewed, and submitted this study.

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