Prediction and mapping of soil organic carbon stock using pedometrical techniques at regional scale.

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Rationale

It is widely documented that carbon (C) sequestration in agricultural soils can play an important role in off-setting industrial CO_2 emissions (Sperow, 2006; Lal, 2004; West and Post, 2002). In this context, knowledge of soil organic carbon (SOC) stock at different spatial scales is essential. Regional assessment of SOC stock is limited due to the lack of adequate field observations which are cost and time constrained.

Objective & hypothesis

To Predict and map the SOC stock to 1- m depth for the State of Indiana using pedometrical techniques.

If the variability in environmental parameters that affect soil development can be captured through soil samples, it is possible to predict the SOC stock reliably and credibly. Environmental variables such as elevation, climatic factors (temperature and precipitation), and land use were used in this study.

Materials & methods

❖ A total of 464 geo-referenced soil profile data representing 204 soil series was collected from the Natural Resources Conservation Service database for the State of Indiana. Additional 48 soil profile samples were collected to better represent the heterogeneity of the environmental variables in the study area (Fig. 1). Two methods were employed to model the depth distribution of SOC stock using negative exponential profile depth functions.

❖ In the first method, the functions to describe the depth distribution of volumetric C content for each soil profile were fitted using the non linear least squares. The parameters of the functions were interpolated for the entire study area using co ordinary kriging. The integral of the exponential function up to the desired depth was used to predict the SOC stock.

❖ In the second method, cumulative SOC stock was estimated for incremental depths in each profile, and the exponential functions were fitted to describe the depth distribution of cumulative SOC stock. The parameters were interpolated using ordinary kriging, and the desired depth was used in the exponential function to estimate the SOC stock.

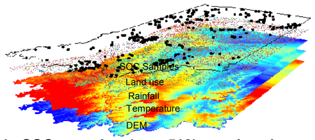

Fig. 1. SOC samples (n = 512) overlayed on environmental parameters.

Fitted exponential function is shown in Eq. 1:

$C = a\exp^{-bZ}$ --Eq.1

where, C is the carbon content, Z is the absolute depth, and a and b are the parameters of exponential functions.

The integral of exponential function (Eq. 2) was used to estimate the SOC stock.

$C_s = \int_0^Z a * e^{-b*Z}$ --Eq. 2

where, Cs is carbon stock (Kg/m²) up to desired depth (Z) in the soil profile.

Validation of SOC estimates:

SOC stock was estimated for each profile of the validation dataset (n = 98) by summing the C stock of each horizon from the surface to the depth of 1m using Eq. 3:

$Cs = \sum_{j=1}^{n}(C_m * \rho_b) * D$ --Eq. 3

where, C_s = carbon storage (Kg/m²), j = soil horizons 1,2,3….n, C_m is carbon concentration on mass basis (kg/Kg), ρ_b is bulk density (Kg/m³) and D is the horizon thickness (m).

Validation indices such as Pearson's correlation coefficient (r), mean estimation error (MEE), and root mean square error (RMSE) were calculated from the observed and predicted SOC stock values. MEE and RMSE were calculated by using Eq. 4 and 5:

$MEE = \frac{1}{n}\sum_{i=1}^{n}(z^*(x_i) - z(x_i))$ --Eq. 4

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(z^*(x_i) - z(x_i))^2}$ --Eq. 5

where, z (x_i) is the measured C concentration, z*(x_i) the estimated C concentration and n the number of validated observations.

Results

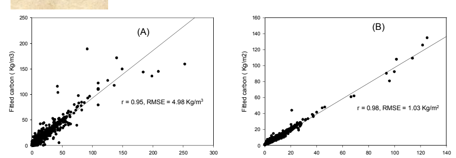

Fig. 2 Observed and exponential depth function fitted SOC stock by first (A) and second method (B) (n = 414 calibration points).

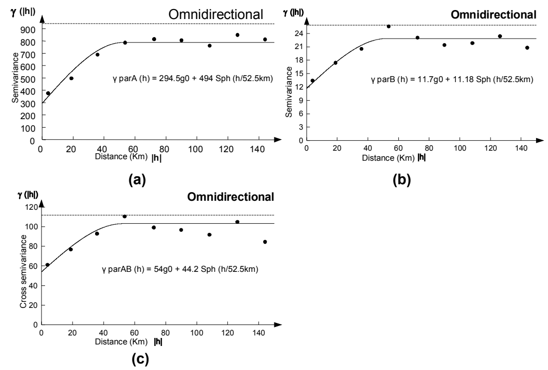

Fig. 3 Experimental variograms and fitted models used for interpolation of parameters a (a), b (b), and cross variogram of both parameters (c) using first method.

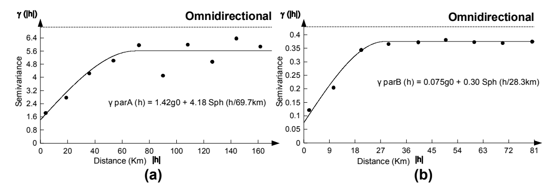

Fig. 4 Experimental variograms and fitted models used for interpolation of parameters a (a), and b (b) using second method.

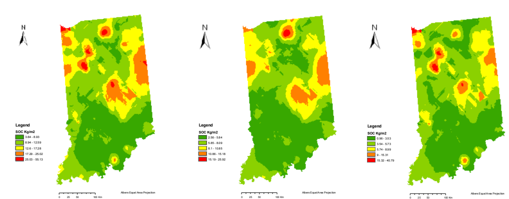

Fig. 5 Predicted SOC stock map (0-1m) (left), surface soil (middle), and sub soil (right) using the second method.

❖ Higher SOC stock in northern part (low temperature, low rainfall, low slope) than the southern part (high temperature, high rainfall, high slope) of state.

❖ SOC is mainly stored in the surface soil but in few areas more SOC is in the sub soil.

Table 1. Validation indices of SOC stock from 0 - 1 m depth using both methods (n = 98 validation points).

Indices / Methods	First method (0-1m)	Second method (0-1m)
Pearson's correlation coefficient (r)	0.64	0.68
MEE (Kg/m²)	-0.86	0.70
RMSE (Kg/m²)	3.93	3.73

Table 2. Validation indices of SOC stock for surface soil and sub soil using both methods (n = 98 validation points).

Indices / Methods	First method		Second method	
	Surface soil	Sub soil	Surface soil	Sub soil
Pearson's correlation coefficient (r)	0.68	0.34	0.75	0.50
MEE (Kg/m²)	-0.10	-1.15	-0.59	1.27
RMSE (Kg/m²)	3.27	2.61	2.89	2.57

Summary & conclusions

❖ Predicting parameters based on exponential function was useful to map the SOC stock at desired depths.

❖ The prediction accuracy showed that the second method of fitting exponential function is a better approach (higher r, lower RMSE) to model the depth distribution of SOC stock.

❖ SOC stock in Indiana is estimated to be 0.915 Pg (1 Pg = 10^{15}g) using major land resource area - land use approach.

❖ The prediction accuracy of the SOC map supports the hypothesis that by sampling across the variability of environmental variables, it is possible to predict the SOC stock with a reasonable accuracy.

❖ Therefore, pedometrical approaches are useful to map the SOC stock at varying spatial scales for different depths.

References

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