

ESTIMATING SOIL PARTICULATE ORGANIC CARBON THROUGH TOTAL SOIL ORGANIC CARBON

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ABSTRACT

Particulate soil organic carbon (POC) is sensitive to management changes, and a good soil health indicator. However, its determination is tedious and time consuming. Given POC changes represent most of total organic carbon (TOC) variation due to soil use, we hypothesized that POC can be estimated through the variation of TOC. Our objective was to evaluate changes of POC and TOC for a wide range of soil silt (Si) + clay (Cy) contents to assess the feasibility of estimating POC through TOC. Soil samples (n=161) were collected from the surface layer of fields under no tillage throughout the Argentinean Pampean Region, and their TOC and POC concentrations were determined. The variation of POC was described with exponential models fitted as a function of both TOC and TOC/(Si+Cy). The models fitted adequately and estimated POC as a function of TOC ($R^2=0,96$, observed vs estimated not different from the 1:1 line). No improvement was observed when POC and TOC contents were relativized to Si+Cy contents ($R^2=0,97$). Approximately 74% of the estimated values of POC deviated less than $\pm 10\%$ from the observed values. We conclude that for the conditions studied, the model acceptably estimated POC knowing TOC hence saving time and resources to assess soil health status.

Key words. Organic matter fractions, soil health indicator, soil texture, modelling.

ESTIMACIÓN DEL CARBONO ORGÁNICO PARTICULADO A TRAVÉS DEL CARBONO ORGÁNICO TOTAL DEL SUELO

RESUMEN

El carbono orgánico particulado (POC) es sensible a los cambios producidos por las prácticas de manejo, resultando un buen indicador de la salud del suelo. Sin embargo, su determinación es tediosa y consume mucho tiempo. Dado que los cambios en POC debido al uso del suelo representan la mayor parte de las variaciones del carbono orgánico total (TOC), se hipotetizó que el POC se puede estimar a través de la variación de TOC. Nuestro objetivo fue evaluar los cambios de POC y TOC en suelos con un amplio rango de contenidos de limo (Li) + arcilla (As) para evaluar la posibilidad de estimar POC a través de TOC. Se recolectaron muestras (n=161) superficiales de lotes bajo siembra directa en la Región Pampeana Argentina, y se les determinó el TOC y el POC. La variación de POC en función de TOC y TOC/(Li+As) fue ajustada con un modelo exponencial. El modelo explicó adecuadamente la variación de POC en función de TOC ($R^2=0,96$, observado vs estimado no diferente de la línea 1:1). No se observaron mejoras cuando los contenidos de POC y TOC fueron relativizados con los contenidos de Li+As ($R^2=0,97$). Aproximadamente el 74% de los valores estimados de POC se desviaron menos de $\pm 10\%$ de los valores observados. Se concluye que para las condiciones estudiadas, el modelo estimó de modo aceptable el POC conociendo el TOC, por lo tanto se ahorraría tiempo y recursos para evaluar el estado de salud del suelo.

Palabras clave. Fracciones de materia orgánica, indicador de salud de suelo, textura del suelo, modelación.

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INTRODUCTION

Soil organic carbon (TOC) is a key soil component for agroecosystem functioning due to its role as a nutrient reservoir and supplier and in soil structure stabilization, among others. However, TOC content is dynamic and strongly affected by management practices that influence carbon (C) loss and sequestration, and dependent on the balance between C gains and losses as affected by soil management (Janzen, 2006).

The Pampean Region of Argentina (30° to 40° S and 57° to 66° O) (Fig. 1) is recognized as one of the most important grain production regions in the world (Álvarez & Steinbach, 2009). In the last decades, the progressive increase of cropping has produced a negative balance of C (Sainz Rozas *et al.*, 2011), nitrogen (N), and other nutrients, with a concomitant deterioration of soil properties increased erosion (Manuel-Navarrete *et al.*, 2009). Despite the steadily increase since the 90's of the

cropping area under no-tillage (NT) (MAGyP, 2011), the increase of the frequency of soybean (*Glycine max* (L.) Merr.) in crop sequences because of its higher profitability, has counterbalanced the expected beneficial effect of NT (Manuel-Navarrete *et al.*, 2009) due to the low amount of C returned to the soil as residues (Studdert & Echeverría, 2000). Soil health indicators are needed to develop management decisions to deal with the delicate equilibrium regulating soil functioning and with the need of a profitable and sustainable agriculture.

The cropping effects on soils can be monitored through the changes in TOC or its fraction contents (Diovisalvi *et al.*, 2008). Particulate organic C (POC) has been proposed as an early indicator of the effects of soil management practices. It shows the size of the easily mineralizable soil organic fraction compartment, and hence is very important to estimate soil N mineralization potential (Fabrizzi *et al.*, 2003; Gregorich *et al.*, 2006). Likewise, POC is closely

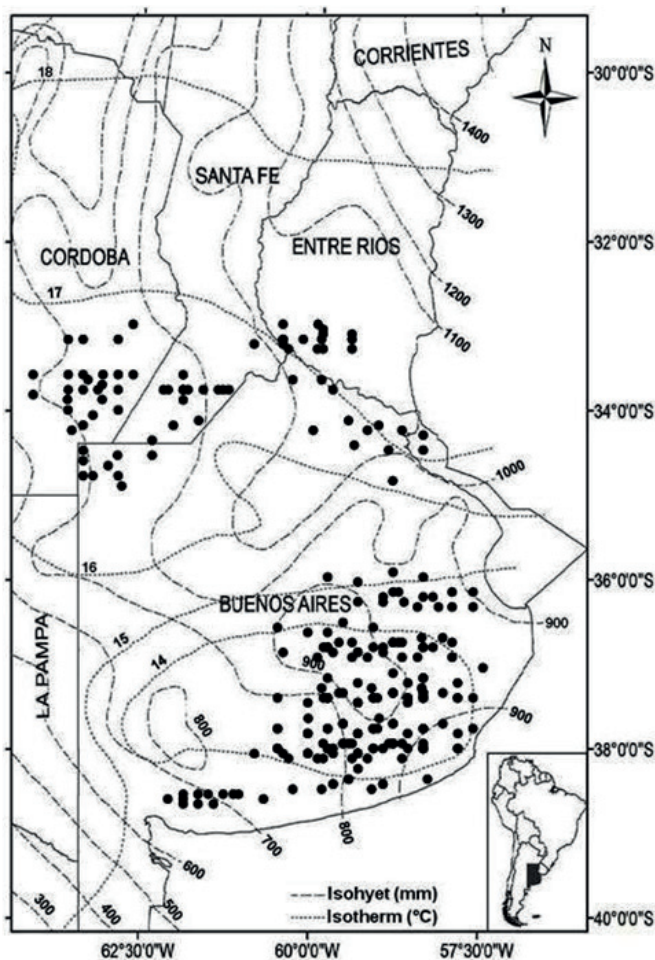


Figure 1. Argentinean Pampean Region map indicating isohyets and isotherms. Dots show the places from where soils samples were taken.
Figura 1. Mapa de la Región Pampeana Argentina indicando isohietas e isotermas. Los puntos indican los lugares en donde fueron tomadas las muestras de suelo.

related to soil structure and stabilization, since its decomposition by microorganisms produces organic compounds that stimulate aggregation, increase macroaggregate stability, and promote long term C stabilization in microaggregates (Six *et al.*, 2004). Therefore, the knowledge of POC content variation would allow predicting soil conditions and crop behavior related to soil management changes (Diovisalvi *et al.*, 2008) and would be an important tool to help make management decisions to stop and revert soil health deterioration.

Even though POC determination is simple, the technique is tedious and time-consuming. Therefore, its use in commercial soil laboratories as a routine method is limited and expensive for producers. It would be important to have an easily measurable estimator of POC content. Results from soils of the Argentine Pampas Region with a wide range of textures show that, in fields where erosion is not important, changes in TOC related to soil use are mainly explained by POC content variations (Diovisalvi *et al.*, 2008; Quiroga *et al.*, 2008; Irizar, 2010). Therefore, it would be feasible to estimate POC content using TOC content and thus avoiding fractionation.

A strong correlation between silt (Si) plus clay (Cy) (Si+Cy) content and TOC has been reported (Quiroga *et al.*, 2006; Zinn *et al.*, 2007), both in cropped and in undisturbed soils (Hassink, 1997; Hevia *et al.*, 2003). Hence, TOC content and C sequestration capacity increase with finer textures (Six *et al.*, 2002; Zinn *et al.*, 2007). The greater the Cy content, the larger the specific surface where humified C can be adsorbed and protected (chemical protection; Six *et al.*, 2002) and therefore, the greater the amount of C associated to the mineral fraction (AOC). Besides, higher Cy content is related to more aggregation, aggregate stability and physical protection of both AOC and POC making it less exposed to mineralization (Six *et al.*, 2002). Hence, soil texture affects the rate and magnitude of TOC fraction changes due to soil use. In order to account for the differential protection of soil organic C associated to texture, indexes like TOC/(Si+Cy) have been proposed to analyze and compare TOC (Quiroga *et al.*, 2006) and its fraction contents and variation among soils with different particle size distributions.

We hypothesize that since POC changes represent most of the variation of TOC, POC changes associated to soil use can be estimated through the variation of TOC. Our objective was to evaluate changes of POC and TOC throughout a wide range of soil textures in order to assess the feasibility of estimating the former knowing the latter.

MATERIALS AND METHODS

Soil samples and sample processing

This study was performed on 161 soil samples from the arable layer (0-20 cm) of fields under NT with different management histories and years under continuous cropping, ranging between null disturbance by cropping and more than 25 years of continuous cropping. Soil samples were collected from different areas of the Pampas Region in Argentina (Figure 1): Southeastern, Southwestern, Central, Northeastern and Northwestern areas of Buenos Aires Province, Southwestern area of Entre Ríos Province, Southern area of Santa Fe Province, and Southeastern area of Córdoba Province. The climate is temperate-humid (18 °C isotherm in the north through 14 °C isotherm in the south) (Figure 1). Its topography is flat to slightly rolling and its soils are predominantly Mollisols originating mainly from loessic sediments and to a lesser extent from fluvial sediments. Therefore, these soils show a wide range of depths, textures, organic matter contents and fertility (Álvarez & Lavado, 1998). In general, soil texture is finer from the Southwest (SW) to the Northeast (NE), coinciding with annual rainfall and mean temperature increments (Figure 1), and the particle size distribution of the parent material (coarser in the SW and finer in the NE). Hence, sandy and sandy-loam Typic and Entic Haplustolls predominate in the West and SW regions, whereas loam, silt-loam and silty-clay-loam Typic and Vertic Argiudolls predominate in the East and NE (Duran *et al.*, 2011).

The contents of TOC, AOC, and POC were determined on each soil sample. The mineral associated fraction (<50 µm) was separated through the fractionation method described by Cambardella & Elliott (1992). Whole soil organic C (TOC) and AOC contents were determined by wet combustion through complete oxidation with potassium dichromate in solution with sulfuric acid maintaining a reaction temperature of 120 °C during 90 min (Schlichting *et al.*, 1995). Particulate organic C content was calculated by subtracting AOC content from TOC content (Cambardella & Elliott, 1992).

The proportion of the different size mineral fractions was determined through a modification of the method described by Gee & Bauder (1986). We used a constant soil aliquot (50 g) regardless of soil texture, instead of 10-20 and 60-100 g for fine-textured soils and coarse-textured soils, respectively, as proposed by Gee & Bauder (1986). Soil samples were grouped in four arbitrary texture classes according to their Si+Cy contents: 1) Fine (>750 g kg⁻¹ Si+Cy) (Fi), 2) Loam fine (>500 g kg⁻¹ - ≤750 g kg⁻¹ Si+Cy) (Lfi), 3) Loam coarse (>250 g kg⁻¹ - ≤500 g kg⁻¹ Si+Cy) (LCo), and 4) Coarse (≤250 g kg⁻¹ Si+Cy) (Co). Nine, 79, 53, and 20 soil samples out of the 161 samples corresponded to the Fi, Lfi, LCo, and Co textural classes, respectively.

Model development and validation

Variations in POC and POC/(Si+Cy) were related to variations in TOC and in TOC/(Si+Cy) through exponential models. Curve fitting was performed through non-linear regression analysis (R Development Core Team, 2009). The model used to fit POC and POC/(Si+Cy) as a function of TOC or TOC/(Si+Cy) was:

$$DVp = -I + I * \exp(r * IV) \quad (\text{Eq. 1})$$

where DVp is the dependent variable (POC (g kg^{-1}) or POC/(Si+Cy) ($\text{g kg}^{-1}/\text{g kg}^{-1}$)), I is the intercept, r is the exponential rate of change ($1/(\text{g kg}^{-1})$ or $1/(\text{g kg}^{-1}/\text{g kg}^{-1})$) and IV is the independent variable (TOC (g kg^{-1}) or TOC/(Si+Cy) ($\text{g kg}^{-1}/\text{g kg}^{-1}$)).

In order to perform the curve-fitting and then the corresponding model performance evaluation, the data set ($n=161$) was randomly split into two sub-sets: 70% of the data was used for curve-fitting and the remaining 30% was used for model validation. When splitting the data set, each textural group was proportionally represented in the resulting sub-sets (fitting and validation). Random data splitting, curve fitting, and model validation were run five times and the model that best performed for each variable relationship was selected.

Model performance evaluation

Several statistic tools were used to evaluate the agreement between the observed and the estimated values of each dependent variable (DV) after the validation process and to choose the model that best described the variation of the DV as a function of the IV. On the one hand, linear simple least square regression analyses of DV observed values on DV estimated values were performed. The equality of the intercept and of the slope to zero and one, respectively, was tested through F-tests both separately and simultaneously.

On the other hand, we calculated the difference between DV observed values and DV estimated values to obtain the bias error (BE), and we calculated the relative error (RE, %) as the quotient between BE's and their corresponding observed values. The BE's and RE's means were referred to as the mean bias error (MBE) and mean relative error (MRE, %), respectively. Root mean squared variation (RMSV) (Kobayashi & Salam, 2000) and root mean squared error (RMSE) (Fox, 1981), were also calculated. All calculations and analyses for model performance evaluation were done on the computational environment of R (R Development Core Team, 2009).

The best models were those with the highest R^2 both in the curve fitting step and in the linear regression between observed and estimated DV values. Likewise, the coefficients of these

linear regressions (intercept and slope) had to be significantly equal to 0 and 1, respectively, both separately and simultaneously. On the other hand, the best model had to have generated the lowest RMSE and RMSV. Normality (Shapiro-Wilk test) and homocedasticity (visual distribution in plot as a function of observed values) of BE (R Development Core Team, 2009) were checked in all cases.

Re-validation with independent data

Soil-surface layer (0-20 cm) TOC and POC contents determined annually between 1994 and 2006 in samples from the a long-term experiment carried out at the *Unidad Integrada Balcarce*, Balcarce, Buenos Aires Province ($37^{\circ}45'S$, $58^{\circ}18'W$, 138 m above sea level), were used to re-validate the selected best models. The soil is a complex of fine, mixed, thermic Typic Argiudoll (USDA, 2006) (*Mar del Plata* series, INTA, 1979) and fine, illitic, thermic Petrocalcic Paleudoll (USDA, 2006) (*Balcarce* series, INTA, 1979) with less than 2% slope (low erosion). Particle size distribution of soil complex was 230, 360, and 410 g kg^{-1} Cy, Si and Sa contents (INTA, 1979), respectively, and the textural class was LFi ($>500 \text{ g kg}^{-1} - d \gg 750 \text{ g kg}^{-1}$ Si+Cy). The experimental design was described by Cozzoli *et al.* (2010). Briefly, the cropping systems included: continuous cropping under NT and under conventional tillage (CT), 25% of the rotation cycle (3 yr) with pasture followed by 75% of the rotation cycle (9 yr) with cropping under NT and under CT, 50% of the rotation cycle (3 yr) with pasture and 50% of the rotation cycle (3 yr) with cropping under NT and under CT, and continuous pasture. Soil TOC and POC contents were determined as described above. Model performances, normality and homoscedasticity were evaluated with the same statistical tools mentioned before.

RESULTS

Table 1 shows the means and coefficients of variation (CV) of Si+Cy, Sa, TOC, AOC and POC contents for all four texture classes defined. It is worth pointing out that the largest number of samples considered for this study was from the medium texture classes (LFi and LCo) which in turn correspond to the most intensively cultivated area of the Argentine Pampas Region.

Curve fitting and model validation with validation data set

In all cases, the exponential model shown as Eq. 1 adequately described ($P < 0,0001$) the variation of the DV as a function of the IV, with very high R^2 (all $> 0,88$, data not shown). The lowest R^2 (between 0,89 and 0,91, data not shown) were achieved by the model fitted to POC as

Table 1. Soil variables for each textural class.

Tabla 1. Variables de suelo para cada clase textural.

Texture class	n ^(a)	Si + Cy ^(a)		Sa ^(a)		TOC ^(a)		AOC ^(a)		POC ^(a)	
		Mean	CV ^(a)	Mean	CV ^(a)	Mean	CV ^(a)	Mean	CV ^(a)	Mean	CV ^(a)
g kg ⁻¹											
Fine	9	839,4	10,1	160,6	52,8	26,8	31,2	17,9	31,7	8,9	39,2
Loam Fine	79	571,0	10,5	429,0	14,0	36,9	23,6	24,2	18,6	12,7	43,1
Loam Coarse	53	387,0	17,1	613,0	10,6	26,9	50,0	16,4	43,1	10,6	70,8
Coarse	20	192,9	22,1	807,1	5,3	11,8	46,2	7,3	45,3	4,5	58,7

^(a) n: number of soil samples, Si+Cy: silt plus clay content, CV: coefficient of variation, Sa: sand content, TOC: total soil organic carbon, AOC: mineral associated soil organic carbon, POC: particulate soil organic carbon.

a function of TOC/(Si+Cy) with Eq. 1, whereas the rest of the relationships had R² above 0,95 (data not shown). However, the validation step showed performance differences among the models generated by the five curve-fitting runs for each DV vs. IV relationship (data not shown). Table 2 shows the results of curve-fitting and model performance of the best model for each DV vs. IV relationship.

As mentioned before, the poorest performance was shown by the models describing the relationship between POC and TOC/(Si+Cy). Even though the R² achieved for this relationship was high (0,90, Table 2), the variation of the estimated values of POC did not explain the variation in the corresponding observed ones adequately (low linear regression R², Table 2 Model validation). That model ten-

Table 2. Curve-fitting (Equation 1) step and model validation step results.

Tabla 2. Resultados del ajuste del modelo (Ecuación 1) y de su validación.

Performance statistics	Independent variable		
	TOC ^(a)	TOC/(Si + Cy) ^(a)	
	Dependent variable		
	POC ^(a)	POC ^(a)	POC/(Si + Cy) ^(a)
Curve fitting			
<i>P</i> > <i>F</i>	<0,0001	<0,0001	<0,0001
R ²	0,96	0,90	0,97
Model validation			
Simple linear regression observed vs. estimated values			
<i>P</i> > <i>F</i> (I=0) ^(a)	0,60	0,41	0,29
<i>P</i> > <i>F</i> (S=1) ^(a)	0,65	0,38	0,19
<i>P</i> > <i>F</i> (I=0 and S=1) ^(a)	0,55	0,50	0,42
R ²	0,88	0,65	0,84
Statistics based on the difference between observed and estimated values			
MBE ^(a) (g kg ⁻¹)	-0,18	-0,03	0,00
MRE ^(a) (%)	-2,40	-21,87	-3,36
RMSE ^(a)	2,15	3,67	0,04
RMSV ^(a)	2,15	3,67	0,04

^(a) TOC: total soil organic carbon, AOC: mineral associated soil organic carbon, POC: particulate soil organic carbon, Si + Cy: silt plus clay content, I: intercept, S: slope, MBE: mean bias error, MRE: mean relative error, RMSE: root mean squared error, RMSV: root mean squared variation.

ded to overestimate POC as a function of TOC/(Si+Cy) since MRE was negative indicating that, on average, estimated values were higher than the observed ones. It is worth remarking that the highest negative MRE values were obtained for the coarser texture classes being -120,7% for Co, and -36,9%, for LCo.

Table 2 shows that the models to estimate POC as a function of TOC, (Fig. 2a) and POC/(Si+Cy) as a function of TOC/(Si+Cy) (Fig. 2b) performed best. Variation of the IV (TOC or TOC/(Si+Cy)) explained more than 95% of the variation of the DV (POC and POC/(Si+Cy)). Likewise, in the validation step, the variation of the estimated values explained most of the variation of the observed ones (R^2 of the simple linear regressions were 0,88 and 0,84, respectively). Table 2 and Figure 3 also show that the li-

near regression models of observed values versus the estimated ones in the validation step were statistically equal to the 1:1 line.

The two models obtained (Fig. 2) tended to slightly overestimate the DV values since MRE values were negative (-2,40 and -3,36%, Table 2), indicating that, on average, estimated values were higher than the observed ones. However, only 10 and 28 % of the estimated values in the validation step showed RE within $\pm 5\%$, and 18 and 41% within $\pm 10\%$. On the other hand, the MRE by texture classes indicate that the models showed the poorest performance for both Fi and Co texture classes (-18,6% and 25,5%, and 34,0% and 23,3%, respectively). However, it is worth to recall that the number of cases of these two textural classes included in this study was low ($n=9$ and

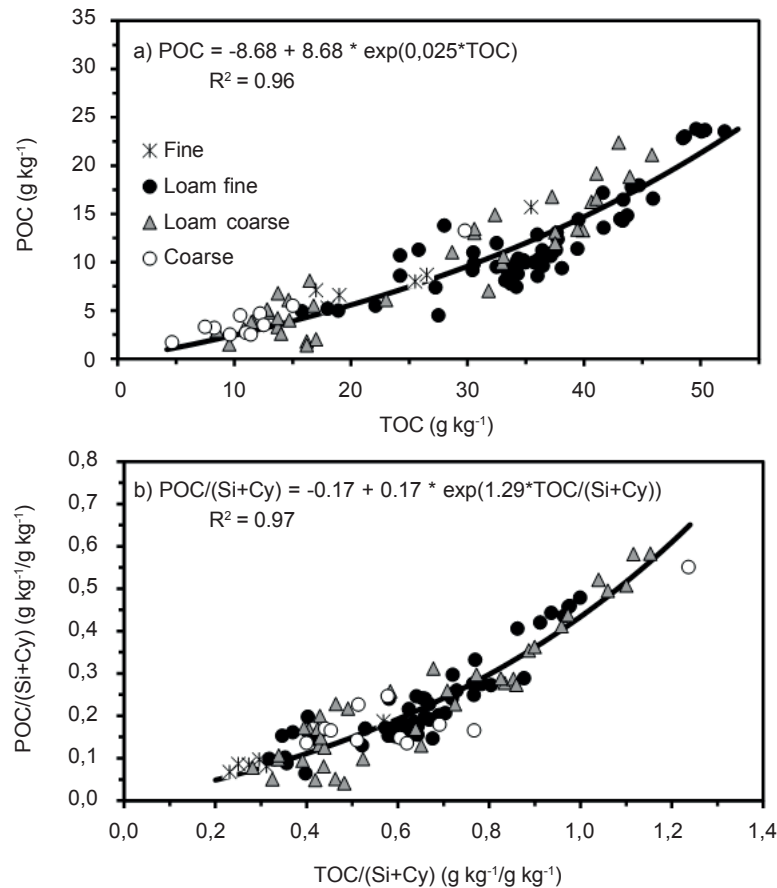
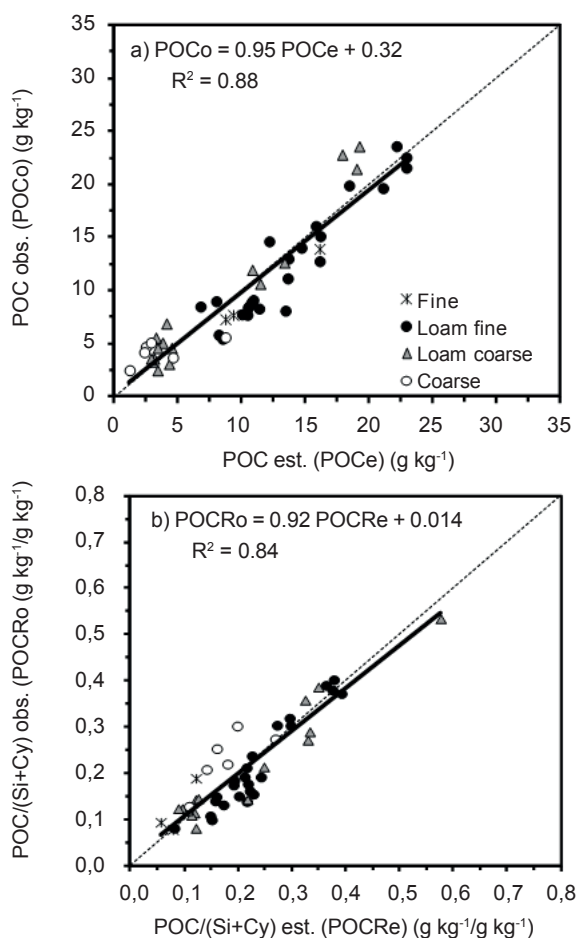


Figure 2. Results of fitting equation 1 to particulate soil organic carbon (POC, a) as a function of total soil organic carbon (TOC) content and to POC relative to silt + clay contents (POC/(Si+Cy), b) as a function of TOC relative to silt + clay contents (TOC/(Si+Cy)).

Figura 2. Resultados del ajuste de la ecuación 1 para los contenidos de carbono orgánico particulado (POC, a) en función de los contenidos de carbono orgánico total (TOC) y para los contenidos de POC relativizados por los contenidos de limo + arcilla (POC/(Si+Cy), b) en función de los contenidos de TOC relativizados por los contenidos de limo + arcilla (TOC/(Si+Cy)).

Figure 3. Results of simple linear regressions between observed (obs.) values in the validation data set of particulate soil organic carbon (POC, a) and POC relative to silt + clay contents (POC/(Si+Cy), b), and the estimated (est.) values with the corresponding models shown in Figure 2. Results of statistical analysis of the regressions are shown in Table 2.

Figura 3. Resultados de la regresión lineal simple entre los valores observados (obs.) en la validación con el set de datos de carbono orgánico particulado (POC, a) y POC relativizado por el contenido de limo + arcilla (POC/(Si+Cy), b), y los valores estimados (est.) con el correspondiente modelo mostrado en la Figura 2. En la tabla 2 se muestran los resultados de la evaluación estadística de las regresiones.



$n=20$, respectively, Table 1) and could have not been representative of a wide enough range of management situations to adequately take into account the real variability.

According to these results (Fig. 2 and Table 2), for the range of textures explored, POC could be satisfactorily predicted with TOC content, especially for soils with loam texture.

Validation with an independent data set

Figure 4 shows the linear regression between the observed values of POC as a function of the estimated ones. This Figure indicates that the model obtained in the curve-fitting step (Fig. 2a) adequately estimated the changes of POC as a function of TOC. Most of the variation of the observed values was explained by the variation in the estimated ones; the R^2 of the linear regressions was 0,67

(Fig. 4). The model tended to overestimate POC since MBE and MRE were slightly negative ($-0,33 \text{ g kg}^{-1}$ and $-4,05\%$, respectively), but 50,5 and 74,2% of the RE for POC were within the ranges of $\pm 5\%$ and $\pm 10\%$, respectively. This means that a great proportion of the estimated values diverged no more than 10% from the corresponding observed ones.

It is worth remarking that both conditions of slope equal to 1 and intercept equal to 0 were not achieved by the linear regressions between observed and estimated values (Fig. 4). The very narrow range of values of POC and TOC in the experiment could have been associated to this apparently not acceptable performance indicator. Values of POC and TOC employed for this validation ranged only between $6.9\text{--}13.0 \text{ g kg}^{-1}$, and $26.2\text{--}36.3 \text{ g kg}^{-1}$, respectively. These ranges are much narrower than those of the data used for model fitting and first validation (Table 2). Anyway,

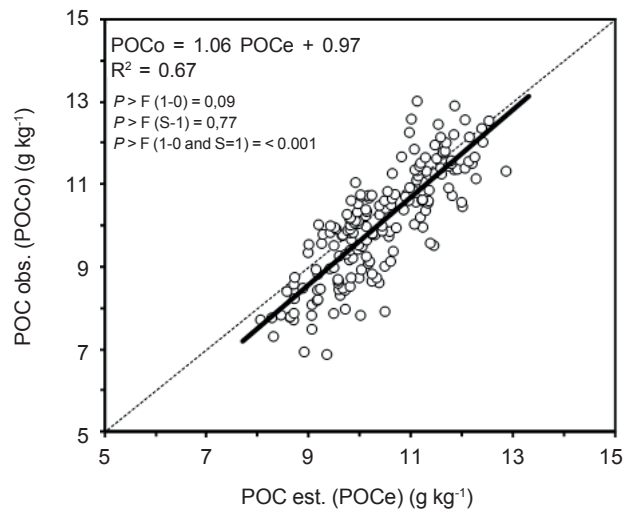


Figure 4. Results of simple linear regressions between observed (obs.) values of particulate soil organic carbon (POC) from a crop rotation and tillage system experiment, and the estimated (est.) values with the model shown in Figure 2a. I: intercept. S: slope.

Figura 4. Resultados de la regresión lineal simple entre valores observados de carbono orgánico particulado (COP) de un ensayo de rotaciones de cultivos y sistemas de labranza, y valores estimados (est.) con el modelo mostrado en la Figura 2a. I: ordenada al origen. S: pendiente.

the rest of the indicators (RMSE=0,83 and RMSV=0.76) denote a good performance of the model fitted to predict POC as a function of TOC (Fig. 2a).

DISCUSSION

Representativeness of the studied soils

The total organic C content range of the soils included in this study (Table 1) is similar to that reported by Sainz Rozas *et al.* (2011) who analyzed TOC content changes in a wide range of soils of the Argentine Pampas Region, and by Puget & Lal (2005) for soils from several parts of the world. The CV of organic C fractions could be attributed not only to particle size distribution within each texture class, but also to the effect of different factors such as cropping history, crop sequence and fertilization which are closely related to soil organic C content. The highest TOC contents were observed in the fine to medium texture classes (Fi, LFi and LCo, Table 1). This agrees with McConkey *et al.* (2003) who reported higher organic C stocks under NT in fine textured soils, which could be attributed to the relationship between Cy content and to the chemical and physical protection of soil organic C (Six *et al.*, 2002). On the other hand, cropping period duration (Studdert *et al.*, 1997; Irizar, 2010) and crop sequence (Domínguez *et al.*,

2009) also affect soil organic C stock through the amount, quality and timing of C input to the soil. The larger the amount of residues returned to the soil, the higher the C input and the lower the effect of soil use on soil organic C stock (Domínguez *et al.*, 2009; Varvel & Wilhelm, 2010). It is worth remarking that the CV of TOC and of AOC were very similar throughout all texture classes (Table 1), whereas those of POC were much higher. This confirms that POC is much more sensitive to different soil management practices and uses.

The wide range of mean TOC and its fractions contents within and among textural classes, together with the dispersion of Si+Cy and Sa contents (Table 1), indicate that soil samples used for this study represent a wide range of situations. Therefore, it is considered that the results of this study are representative of the Argentine Pampas Region.

Prediction of POC

The results shown in Table 2 indicate that the estimation of POC as a function of TOC/(Si+Cy) would not be feasible, especially for coarse textured soils (data not shown). On the other hand, models fitted in the curve-fitting step adequately estimated POC as a function of TOC, and POC/(Si+Cy) as a function of TOC/(Si+Cy) (Table 2).

Plante *et al.* (2006) observed that the relationship of texture with soil organic C differences among soils was higher for those fractions protected within microaggregates than for those labile or hydrolysable ones not occluded within them. This is probably due to the close relation between soil C and Si+Cy content (Hassink, 1997) which in turn also influences microraggregate formation and stabilization (Six *et al.*, 2002). Likewise, McLauchlan (2006) reported that soil organic C increase with the increase in Cy content was not generalized and that only the organic C fraction chemically protected by Cy (Six *et al.*, 2002) followed that trend. Similarly, Liang *et al.* (2009) and Zinn *et al.* (2007) found that soil organic C content was strongly affected by Si+Cy content, especially Cy content. Thus, as proposed by Quiroga *et al.* (2006), the relativization of organic C fraction contents to Si+Cy contents to compare organic C dynamics among soils with different textures would be necessary to account for the influence of the mineral fraction on C dynamics.

As discussed before, in this study, the relativization IV ($TOC/(Si+Cy)$) only did not yield a good estimation of POC (Table 2). Silt+Cy content influences not only the TOC content but also TOC fraction proportions (Plante *et al.*, 2006) and, therefore, partial relativization may have not taken such effect completely into account. However, no improvement in model performance was observed when POC and TOC contents were relativized to Si+Cy contents, when compared to the performance of the model obtained with the not-relativized variables (Figs. 2 and 3, Table 2).

Some other factors could influence the relationship between soil organic C fractions and Si+Cy content such as Cy type, climate factors such as temperature and precipitation, and management practices, among others. Hevia *et al.* (2003) reported that in soils from the Argentine semiarid region, $POC/(Si+Cy)$ increased with increasing annual rainfall whereas it decreased with mean temperature increases. On the other hand, Percival *et al.* (2000) observed in New Zealand that neither Cy content nor climate factors explained the variation of soil organic C, while the proportion of alophans in the Cy fraction explained a great part of it. They concluded that Cy mineralogy highly influences the relationship between Cy content and organic C variation. Furthermore, Hao & Kravchenko (2007) reported that the relationship between organic C fractions and Si+Cy content under NT was much stronger than under CT. Chivenge *et al.* (2006) informed that in fine-textured soils, conservation practices increased

soil organic C due to a reduction of its mineralization rate, while in coarse-textured ones the increase was due to a greater C input. For soils within the LFI texture class, Roldán (2011) reported that higher Cy contents were associated with greater organic C protection and macroaggregate stability regardless of the tillage system.

The soils used in this study represented a wide range of management histories, climatic conditions, and textures (Table 1, Fig. 1). The lack of improvement of model performance when variables were relativized (Fig. 2 and Table 2) indicate that the incidence of climatic and management factors on organic C differences across soils was much stronger than the Si+Cy content effect.

CONCLUSION

The results obtained in this study indicate that for the conditions studied, the fitted model satisfactorily estimated POC using TOC content, especially for soils with loam texture. This reveals a great simplification to obtain POC and with it, estimate some other soil properties important to evaluate soil quality (e.g. N mineralization capacity, aggregate stability). However, even though these results are applicable to the most cropped areas, it is necessary to deepen the research in coarser and finer textured soils. This will contribute to improve the model performance and to have a better representation of most soils, being also very important in terms of their contribution to global crop production.

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