

**Towards realistic and feasible soil organic carbon inventories: a case of study in the Argentinean Semiarid Chaco**

Villarino, Sebastián Horacio<sup>1, 2, \*</sup>, Studdert, Guillermo Alberto<sup>2</sup>, Lattera, Pedro<sup>1, 3</sup>

<sup>1</sup> Consejo Nacional de Investigaciones Científicas y Técnicas (CONICET)

<sup>2</sup> Unidad Integrada Balcarce, Facultad de Ciencias Agrarias (UNMdP) - Estación Experimental Agropecuaria Balcarce (INTA)

<sup>3</sup> Fundación Bariloche

\* presenting author with an asterisk

---

**Abstract**

Soil organic carbon (SOC) is the main terrestrial carbon reservoir. The development of reliable tools for SOC stock monitoring at large scale is fundamental to face climate change. The IPCC carbon inventory method is based on three tiers. The higher the tier, the greater the estimation accuracy, but also the need for resources. Argentinean Semiarid Chaco (ASC) is a deforestation hotspot. In order to improve SOC stocks estimations in that region, we developed a Tier 2 (T2) following a proposed approach for regions with information limitations. The RothC model was used to derive SOC change factors and empirical data was used to estimate SOC under native forest (SOCref). Selected models to predict stock change factor for cropland (Fc) and for grassland (Fg) showed very good fit ( $R^2 = 0.89$  and  $R^2 = 0.90$ , respectively). Hence, SOC changes simulated with RothC could be predicted with linear models. The stock change factors (Fc and Fg) for forest to cropland and forest to grassland conversions were always less than 1. This indicates that deforestation, whether for grassland or cropland land use, decreased SOC stocks. We proved that T2 based on RothC simulations approach could be applied in ASC, a region with information limitations.

*Keywords: IPCC, Tier 2, Greenhouse gas, Land use change, deforestation.*

**Introduction**

The most important anthropogenic greenhouse gas (GHG) is the CO<sub>2</sub>, and its main sources from human activity are primarily from fossil fuel emissions and secondarily from net land use change emissions (IPCC, 2013). Soil organic C (SOC) stock is the main terrestrial C reservoir and land use change generate CO<sub>2</sub> fluxes from soil to atmosphere (Lal, 2011). Thus, in the context of international policy agendas on GHG emissions mitigation, the development of reliable tools for SOC stock monitoring at large scale is fundamental (Lal, 2011).

The Intergovernmental Panel on Climate Change (IPCC) developed a C inventory method (IPCC-CIM) to estimate CO<sub>2</sub> emissions from soil (IPCC, 2006). The IPCC-CIM is based on three tiers. The higher the tier, the greater the accuracy of the outputs, but also the need for knowledge and information (IPCC, 2006). Tier 1 (T1) is easily applicable but, unfortunately, its estimates showed a very poor match with observed data at regional scale (Berhongaray and Álvarez, 2013; Villarino *et al.*, 2014). On the other hand, Tier 2 (T2) and Tier 3 development require the availability of much more information resources and, therefore, they would be feasible only in special and limited cases.

In response to T1 limitation, Villarino *et al.* (2014) proposed a T2 based on simulations performed with the RothC model (Coleman and Jenkinson, 1996). By using this approach, a significant improvement was obtained over T1 for Argentinean Pampa Region with very little demand for additional information (Villarino *et al.*, 2014). In regions where information about SOC stock relations with land use changes is scarce, the

development of a T2 based on that proposed estimation mechanism, could be a good option to improve SOC stock estimations using the IPCC-CIM.

In South American Semiarid Chaco has occurred the highest rate of subtropical forest loss in the 21st century (Hansen *et al.*, 2013), and approximately 62% of this region is located in Argentinean Semiarid Chaco (ASC) (Vallejos *et al.*, 2014). The ASC region is a vast plain of about 29 Mha located at north-central Argentina. Native vegetation of this region is mainly a xerophytic forest. Deforestation rates in the ASC have increased exponentially since 1976, reaching a maximum value (2.5 % yr<sup>-1</sup>) between 2006 and 2012 (Vallejos *et al.*, 2014). The main goal of this work was to test the suitability of the IPCC T2 based on RothC simulations (Villarino *et al.*, 2014) to estimate SOC stocks along land use change in ASC.

## Methodology

The T2 developed was based on Villarino *et al.* (2014) proposal (Eq. 1):

$$\text{SOC} = \text{SOC}_{\text{in}} \times F_i \quad (\text{Eq. 1})$$

where SOC is the estimated SOC stock (Mg ha<sup>-1</sup>), SOC<sub>in</sub> is the initial SOC (Mg ha<sup>-1</sup>), F<sub>i</sub> is the stock change factor for the i-th land use (i.e. cropland or grassland).

Forty counties belonging to ASC were evaluated in 1976, 1996 and 2012. Land use change was classified into seven categories: forest remaining forest, forest to cropland, forest to grassland, cropland remaining cropland, cropland to grassland, grassland remaining grassland and grassland to cropland. Forest change area was obtained from remote sensing estimations (Vallejos *et al.*, 2014) and cropland area was taken from the Argentinean Integrated Agricultural Information System (SIIA, 2015). It was assumed the area that is not neither cropland nor forest, is grassland.

The SOC stock under native forest (SOC<sub>ref</sub>) was estimated with linear models that predict SOC<sub>ref</sub> as a function of soil sand content and mean annual precipitation. Data for model fitting was obtained from soil samples (Villarino *et al.*, 2017) and from climate (Bianchi and Cravero, 2010) and soil maps (INTA, 1990; Angueira *et al.*, 2007).

The stock change factor for croplands (F<sub>c</sub>) and for grasslands (F<sub>g</sub>) were developed from SOC simulations with RothC model. For cropland simulations, 11 hypothetical crop rotations that included cotton, maize, soybean, sunflower, and wheat were defined for the ASC, based on querying to local experts. These rotations were simulated with three rotation yield levels and under two tillage systems (full tillage and no-till). Carbon inputs were estimated from crop yields. The RothC model simulates SOC stock change under full tillage. To simulate no-till system, soil surface condition was loaded in the model as permanently covered. For grassland simulations, we assumed that dry matter (DM) productivity of grasslands was 4.6, 5.7, and 6.7 Mg DM ha<sup>-1</sup> when mean annual precipitation of the county was between 487-642 mm, 643-797 mm, and 798-875 mm, respectively (De León, 2004).

All scenarios were simulated at 0-30 cm soil depth, under three soil clay percentage levels (3%, 13 % y 20 %), and during 10, 20, 30, 40, and 50 years. The average age of a new grassland or cropland area within a period was calculated as the difference between the ending and the starting years of the period divided by two (Villarino *et al.*, 2014). The starting points for croplands simulations were forest at equilibrium, estimated with the inverse mode of RothC model and for grassland simulations were five initial SOC stocks obtained from cropland simulations (55, 42, 36, 30, and 18 Mg C ha<sup>-1</sup>). With all possible combinations, 2970 data of F<sub>c</sub> and 675 data of F<sub>g</sub> were obtained. Then, multiple linear regression models were fitted to predict F<sub>c</sub> or F<sub>g</sub> using soil clay content (g 100 g<sup>-1</sup>), cotton, maize, soybean, sunflower, and wheat proportions (%) in the rotation, weighted average yield (average of each crop yield weighted by the proportion of each one in the rotation), initial SOC stock, elapsed time under cropland or grassland, tillage system, and DM production level as predicting variables. Finally, the best model was selected through graphical analyses of the residuals and the highest R<sup>2</sup> criterion.

## Results

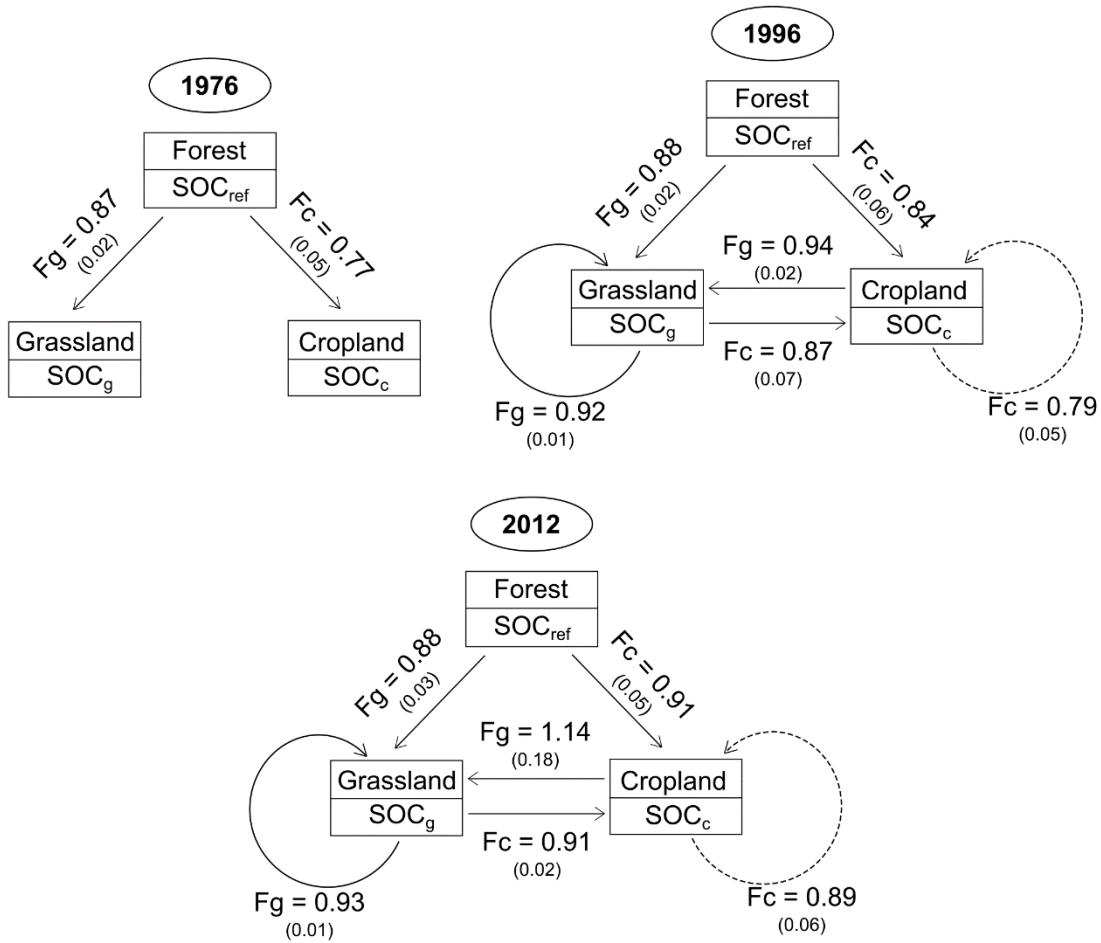
Selected models to predict Fc and Fg showed very good fit ( $R^2 = 0.89$  and  $R^2 = 0.90$ , respectively, Table 1). Hence, SOC changes simulated with RothC could be predicted with linear models (Table 1).

**Table 1: Summary of fitted linear models to predict stock change factor for croplands (Fc) and for grassland (Fg)**

Response variable	Predictor variable	Estimated parameter	Standard error	p-value
Fc	Intercept	5.422	0.307	<0.000001
	Clay (g 100 g <sup>-1</sup> )	0.001352	0.000136	<0.000001
	Time (yr)	-0.00788	0.000102	<0.000001
	Soybean (%)	-0.04536	0.003065	<0.000001
	Maize (%)	-0.04549	0.003065	<0.000001
	Wheat (%)	-0.04302	0.003054	<0.000001
	Sunflower (%)	-0.04436	0.003089	<0.000001
	Cotton (%)	-0.04568	0.003071	<0.000001
	Weighted yield (Mg ha <sup>-1</sup> )	0.04594	0.001176	<0.000001
	SOCi (Mg ha <sup>-1</sup> ) <sup>2</sup>	-0.000058	0.000001	<0.000001
	NT	0.05165	0.003589	<0.000001
	Time (yr) * NT	0.001962	0.000135	<0.000001
Fg	Intercept	1.312	0.01957	<0.000001
	Time (yr)	0.00779	0.000466	<0.000001
	SOCi (Mg ha <sup>-1</sup> )	-0.02081	0.000844	<0.000001
	SOCi <sup>2</sup> (Mg ha <sup>-1</sup> ) <sup>2</sup>	0.000204	0.00001	<0.000001
	DM-5.7	0.05383	0.0045	<0.000001
	DM-6.7	0.1058	0.004522	<0.000001
	Clay (g 100 g <sup>-1</sup> )	0.007798	0.001287	<0.000001
	Clay <sup>2</sup> (g 100 g <sup>-1</sup> ) <sup>2</sup>	-0.000156	0.000056	0.00526
	Time (year) * SOCi (Mg ha <sup>-1</sup> )	-0.000262	0.000013	<0.000001

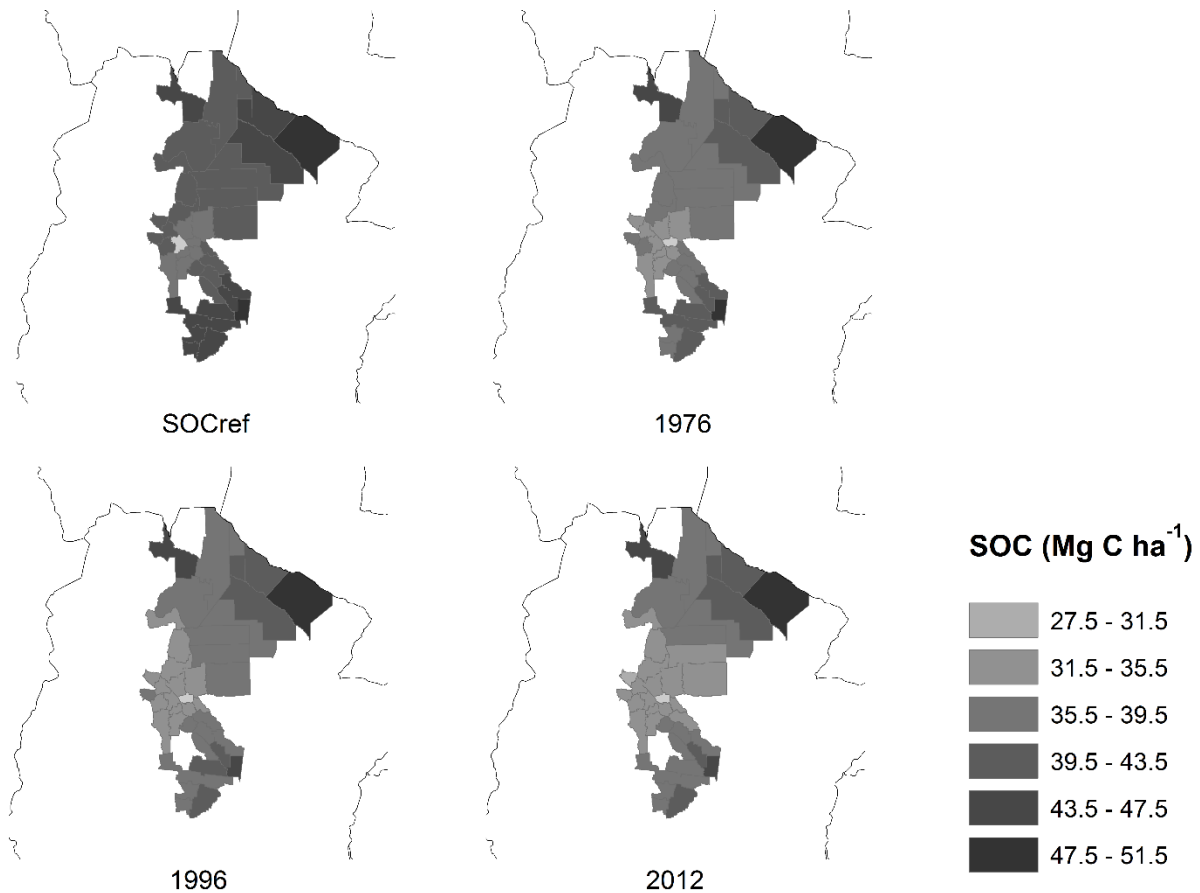
SOCi: initial soil organic carbon. NT, DM-5.7, and DM-6.7 are categorical variables. For croplands under no-till (NT) system, NT = 1, and under full tillage NT = 0. For grasslands, when dry matter (DM) production is 4.6 Mg DM ha<sup>-1</sup>, DM-5.7 = 0 and DM-6.7 = 0, when DM production is 5.7 Mg DM ha<sup>-1</sup>, DM-5.7 = 1 and DM-6.7 = 0, and when DM production is 6.7 Mg DM ha<sup>-1</sup> DM-5.7 = 0 and DM-6.7 = 1. The asterisk (\*) indicates interactions between predictor variables. The adjusted R<sup>2</sup> of Fc and Fg models were 0.89 and 0.90, respectively.

The stock change factors (Fc and Fg) for forest to cropland and forest to grassland conversions were always less than 1. This indicates that deforestation, whether for grassland or cropland land use, always decreased SOC stocks (Fig. 1). The Fg for forest to grassland conversion was between 0.87 and 0.88 and the Fc for forest to cropland conversion was between 0.77 and 0.91 (Fig. 1). The Fc for cropland remaining cropland was always lower than the Fg for grassland remaining grassland (Fig. 1). This means that cropland remaining cropland loss more SOC proportions than grassland remaining grassland.



**Fig. 1: Stock change factors for croplands (Fc) and for grasslands (Fg) used to estimate soil organic carbon changes in grassland (SOC<sub>g</sub>) and cropland (SOC<sub>c</sub>) for each evaluation year (bold number inside ovals). Circular arrows indicate grassland remaining grassland (solid) and cropland remaining cropland categories (dashed). SOC<sub>ref</sub>: soil organic carbon under forest. Number between brackets are the standard deviation.**

The highest SOC<sub>ref</sub> stocks were estimated for the north-east and south-east, whereas the lowest SOC<sub>ref</sub> stocks were estimated for the center-east of the ASC. Between 1976 and 2012, the average SOC stocks were estimated as maintained similar to SOC<sub>ref</sub> in north and south of ASC, whereas a tendency to SOC decrease was estimated in the central ASC (Fig. 2).



**Fig. 2: Soil organic carbon under forest (SOCref) and average soil organic carbon (SOC) stocks in the Argentinean Semi-arid Chaco counties in 1976, 1996 and 2012.**

## Discussion

The  $F_c$  for forest to cropland conversion grew from 1976 through 2012 (Fig. 1). This could be explained by the model parameters in the  $F_c$  model (Table 1). The positive value of weighted yield parameter (Table 1) indicates a positive correlation between SOC stocks and crop yields, and these last grew from 1976 to 2012 (SIIA, 2015). On the other hand, switching from full tillage to no-till strongly affects SOC dynamics and, in many situations, causes a SOC accumulation near soil surface (West and Post, 2002). In agreement with this, the estimated parameter for no-till was positive (Table 1). No-till system was introduced in the 1990s. Hence, this tillage system change led to an increase in  $F_c$  in 2012.

For 16, 10 and 8 yr under cropping after deforestation,  $F_c$ 's of 0.75, 0.85 and 0.90, respectively, were estimated in ASC from observed data (Villarino *et al.*, 2017). The  $F_c$ 's estimated in this work for these cropping ages were 0.77, 0.84 and 0.91 (Fig. 1). Therefore, there is a high degree of agreement between studies. The  $F_g$  for forest to grassland conversion was between 0.87 and 0.88. Caruso (2008) studied 11 sites in ASC where forest changed to grassland, and the average SOC change under grassland was -24% ( $F_g = 0.76$ ). However, this average resulted from an extremely high range, with a maximum of 6% ( $F_g = 1.06$ ) and a minimum of -43% ( $F_g = 0.57$ ). In other ASC sites, Ciuffoli, (2013) observed -30 and -10 % SOC changes for 4 and 31 yr since forest to grassland conversion, respectively ( $F_g$  between 0.7 and 0.9). Hence, these studies (Caruso, 2008; Ciuffoli, 2013) suggest that forest to grassland conversion leads to highly

variable SOC changes. Nevertheless, the Fg's estimated in this work (Fig. 1) have a moderate degree of agreement with the observed values (Caruso, 2008; Ciuffolli, 2013).

## Conclusions

In this work we proved the IPCC T2 based on RothC simulations approach (Villarino *et al.*, 2014) could be applied in ASC, a region with information limitations. The estimated stock change factors of T2 were similar to the reported in other studies carried out in ASC. We encourage to countries or regions that are using T1 due to data limitation to derive a similar T2 method using our proposed approach.

## References

- Angueira, M.C., Prieto, D.R., López, J., Barraza, G., 2007. SigSE: Sistema de Información Geográfica de Santiago del Estero. Version 2.0 en CD ROM. INTA EEA Santiago del Estero.
- Berhongaray, G., Álvarez, R., 2013. The IPCC Tool for predicting soil organic carbon changes evaluated for the Pampas, Argentina. *Agriculture, ecosystems & environment* 181, 241-245.
- Bianchi, A.R., Cravero, S.A.C., 2010. Atlas climático digital de la república argentina. Ediciones INTA, Instituto Nacional de Tecnología Agropecuaria, Buenos Aires, Argentina.
- Caruso, V., 2008. Evaluación de la sustentabilidad ambiental mediante indicadores del uso de la tierra en sistemas ganaderos del chaco salteño. Magister Scientiae Thesis. Universidad Nacional de Mar del Plata.
- Ciuffolli, L., 2013. Cambios en el uso del suelo y sus efectos sobre la materia orgánica edáfica en bosques semiáridos del Chaco argentino. Bachelor's degree Thesis. Universidad de Buenos Aires, Buenos Aires, Argentina.
- Coleman, K., Jenkinson, D., 1996. RothC-26.3-A Model for the turnover of carbon in soil. In: Powlson, D., Smith, P., Smith, J. (Eds.), *Evaluation of soil organic matter models*. Springer, Berlin, Heidelberg, Germany, pp. 237-246.
- De León, M., 2004. Ampliando la frontera ganadera. Las pasturas subtropicales en la región semiárida central del país. Informe técnico. Ediciones INTA, Córdoba, 1-28.
- Hansen, M.C., Potapov, P.V., Moore, R., Hancher, M., Turubanova, S., Tyukavina, A., Thau, D., Stehman, S., Goetz, S., Loveland, T., 2013. High-resolution global maps of 21st-century forest cover change. *Science* 342, 850-853.
- INTA, 1990. Atlas de Suelos de la República Argentina. Ediciones INTA, Instituto Nacional de Tecnología Agropecuaria, Buenos Aires, Argentina.
- IPCC, 2006. Agriculture, Forestry and Other Land Use. In: Eggleston, H., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. (Eds.), *2006 IPCC Guidelines for National Greenhouse Gas Inventories*. IGES, Japan, p. 680.
- IPCC, 2013. Summary for Policymakers. In: Stocker, T., Qin, D., Plattner, G., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P. (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1-30.
- Lal, R., 2011. Sequestering carbon in soils of agro-ecosystems. *Food Policy* 36, S33-S39.
- SIIA, 2015. Sistema Integrado de Información Agropecuaria. Dirección de Información Agrícola y Forestal. Available at: [http://www.siaa.gob.ar/sst\\_pcias/estima/estima.php](http://www.siaa.gob.ar/sst_pcias/estima/estima.php) (accessed 26 January 2017).
- Vallejos, M., Volante, J.N., Mosciaro, M.J., Vale, L.M., Bustamante, M.L., Paruelo, J.M., 2014. Transformation dynamics of the natural cover in the Dry Chaco ecoregion: a plot level geo-database from 1976 to 2012. *Journal of Arid Environments* 123, 3-11.
- Villarino, S.H., Studdert, G.A., Baldassini, P., Cendoya, M.G., Ciuffolli, L., Mastrángelo, M., Piñeiro, G., 2017. Deforestation impacts on soil organic carbon stocks in the Semi-arid Chaco Region, Argentina. *Science of The Total Environment* 575, 1056-1065.
- Villarino, S.H., Studdert, G.A., Lateral, P., Cendoya, M.G., 2014. Agricultural impact on soil organic carbon content: Testing the IPCC carbon accounting method for evaluations at county scale. *Agriculture, Ecosystems & Environment* 185, 118-132.
- West, T.O., Post, W.M., 2002. Soil organic carbon sequestration rates by tillage and crop rotation. *Soil Science Society of America Journal* 66, 1930-1946.