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Agricultural impact on soil organic carbon content: Testing the IPCC carbon accounting method for evaluations at county scale

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ABSTRACT

Soil organic carbon (SOC) plays a vital role in determining soil quality and health, but also SOC decrease contributes significantly to the increase in atmospheric CO_2 concentration. Countries need to quantify their SOC stocks and flows in order to assess their greenhouse gas emissions. To facilitate this, the Intergovernmental Panel on Climate Change has developed a simple carbon accounting method to estimate SOC stocks and flows in response to changes in land use. This method proposes three tiers for SOC change estimation. The higher the tier the greater the accuracy of the estimates, but also the complexity and the need of information. We used the RothC model to derive SOC change factors in order to develop a Tier 2 (T2) method. We applied this T2 and Tier 1 (T1) methods to estimate SOC stocks and flows in five sub regions of the Argentinean Pampa Region between 1900 and 2006. We evaluated T1 and T2 methods performances comparing their estimates against empirical data, at sub region and county scales. At both spatial scales, T1 method showed a poor performance and an important improvement was achieved with T2 method, although its performance varied among spatial scales. At sub region scale, T2 method estimates were very good (R^2 = 0.85), but at county scale the fit was poor (R^2 = 0.46). However, this poor fit may have been due, at least in part, to the quality of the input and validation information of one of the sub regions (Flooding Pampa) since its exclusion of the analysis led to an increase of the R^2 up to 0.73. Tier 2 was used to estimate the impact of land use change on SOC. Sub regions with the highest estimated SOC losses were Central Pampa, Southern Pampa – Eastern and Rolling Pampa, with 35%, 28% and 26% average SOC losses, respectively. Given that several conceptual limitations of T1 method were overcome with our simple T2 method, we conclude that T2 method is more realistic to conduct a regional SOC inventory. Besides, our T2 method was developed without using empirical information from field or laboratory studies about SOC change and, therefore, countries that have not enough empirical information available on SOC change associated to land use could derive a similar T2 method.

1. Introduction

The largest anthropogenic factor contributing to climate change is the carbon (C) dioxide (CO_2) emissions from human activities. Land use change influences ecosystem processes that affect CO_2 fluxes between the atmosphere and ecosystems (Franzluebbers, 2005). For the 1990s, the flux of CO_2 to the atmosphere due to land use change was 1.6 Pg C yr^{-1}. Within the CO_2 emission sources due to human activity, this one is the most important after fossil fuel burning and cement production (Denman et al., 2007).

The most important reserve of C in agricultural ecosystems is held in soil organic matter (Janzen, 2004). However, the importance of organic matter is not only related to its nature of "C source" and "C sink", but also it influences many ecosystem functions such as water retention, resistance to degradation and erosion, nutrient provision for plants and regulation of soil biological activity (Weil and Magdoff, 2004; Martinez et al., 2008; Powlson et al., 2011). Hence, the increase of soil organic carbon (SOC) levels in agricultural systems generates "win-win" situations because it simultaneously reduces CO_2 levels and enhances fertility, productivity and resilience of soil (Díaz-Zorita et al., 2002; Cerri et al., 2004; Freibauer et al., 2004; Lal, 2004; Ogle et al., 2004; Paustian et al., 2004).

The countries listed in the Annex I of the Kyoto protocol compromised to report their GHGs emissions, like CO_2, Methane (CH_4) and Nitrous Oxide (N_2O). Therefore they need a methodology for

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monitoring SOC changes since the emission of such gasses is related to SOC mineralization. Despite this, techniques to quantify SOC changes in large spatial scale are poorly developed (Tate et al., 2004; Wander and Nissen, 2004) and this creates uncertainty about the implications of land use changes on SOC.

The Intergovernmental Panel on Climate Change (IPCC) has published the *2006 Guidelines for National Greenhouse Gas Inventories* (IPCC, 2006a) to accomplish national compilations of GHGs emissions, including CO_2 emissions. The aim of this guidance is that any country, regardless of the experience or resources available, should be able to produce reliable estimates of their emissions and removal of these gases (IPCC, 2006a). The Volume 4: "Agriculture, Forestry and Other Land Uses" describes a carbon accounting method (CAM) to estimate SOC stocks and flows in response to changes in land use (IPCC, 2006b). Nevertheless, it is recognized that the "*Agriculture, Forestry and Other Land Uses*" sector, and particularly the soils section, is one of the most complex and least developed (Lokupitiya and Paustian, 2006).

The CAM proposes three tiers for SOC change estimation. The higher the tier the greater the accuracy of the estimates, but also the complexity and the need of information to estimate SOC changes and flows (IPCC, 2006c). With Tier 1 (T1) method SOC change estimates are calculated as the difference in SOC stock between two moments. The SOC stocks are estimated by assigning a reference SOC (SOCref) content, which would represent that under native vegetation, and then multiplying this value by default stock change factors which depend on land use. Tier 2 (T2) method uses the same equations as T1 method, but SOCref and stock change factors to be used are derived from local data. Finally, Tier 3 (T3) method includes more complex models and inventory measurement systems driven by high-resolution activity data that better capture variability for local conditions (IPCC, 2006d; Ravindranath and Ostwald, 2008). The IPCC recognizes the limitations of using global and regional default values (T1 method) and, therefore it encourages countries to derive their own T2 or T3 method. Nevertheless, most of the countries listed in Annex I used T1 method to report their CO_2 emissions (Lokupitiya and Paustian, 2006). The main limitation is the availability of the adequate information about impact of land uses change on SOC.

Tiers 1 and 2 methods estimate the direct effect of land use change and management on SOC through three simple stock change factors derived from data set of experimental results (IPCC, 2006d). On the other hand, SOC dynamics models are based on empirical relationships developed from field and laboratory studies to simulate the process that influences SOC changes. Thus, simulation models would provide a more complete accounting of SOC changes but at the same time, are more complex and much more difficult to implement for purposes of conducting a national inventory (Ogle and Paustian, 2005) and therefore T3 would be feasible only in special and limited cases. Despite this, in order to improve the reliability of estimations and to be useful for conducting a national inventory at the same time, we believe that the results of complex SOC simulation models could be used to estimate coefficients of more simple models. The RothC model (Jenkinson et al., 1987) is a widely used SOC change estimation model and has been evaluated under many conditions with good general results (Coleman et al., 1997; Smith et al., 1997; Falloon and Smith, 2002; Cerri et al., 2007).

In Argentina, T1 method has been used by Viglizzo et al. (2011) to estimate SOC changes for the period 1956–2005, but these results have not been evaluated against empirical data. On the other hand, Berhongaray and Alvarez (2012) and Berhongaray et al. (2013), contrasted the results of the application of T1 method against empirical data from the Argentinean Pampa Region (APR). These authors concluded that T1 method was not a valid model to estimate SOC changes and flows in the APR and they recommended using local data in order to develop a T2 method. Despite this, until now, no one has developed a T2 method for Argentina or for the APR.

On a world basis, in 2011 Argentina was the 3rd soybean producer, the 3rd sunflower producer, the 5th maize producer and the 12th wheat producer (FAO, 2012). The APR is the main cropping region of the country (Hall et al., 1992), occupying approximately 26% of its surface (INDEC, 2004). Since this region has a long history of agriculture there is a great amount of research information about the effect of management practices on SOC changes (Lavado et al., 1996; Studdert et al., 1997; Steinbach and Alvarez, 2006; Urioste et al., 2006; Bono et al., 2008; Alvarez and Steinbach, 2009), together with census and survey data (INDEC, 1964, 1991, 2004; SIIA, 2013) that are potentially utilizable for the development and calibration of a T2 method.

Therefore, we have posed three specific goals for this article:

(i) Generate a T2 method using local information and RothC to derived SOC stock change factors.
(ii) Evaluate this T2 method to estimate the agricultural impact on SOC, since 1900 until 2006 in the APR, and compare its accuracy with T1 method.
(iii) Provide a guide to develop a T2 method to be used for any region or country with a minimum requirement of input data.

2. Materials and methods

2.1. Site

The native vegetation of the APR is mainly composed by grasses of C3 and C4 *Poaceae* species (Burkart et al., 1988; Soriano, 1991). In the last century, a large proportion of these grasslands has been transformed into croplands or cultivated pastures (Hall et al., 1992; Baldi et al., 2006; Viglizzo et al., 2010).

We divided the APR into five sub regions: Rolling Pampa, Southern Pampa (with two subunits, Eastern (E) and Western (W)), Flooding Pampa and Central Pampa (Fig. 1). These sub regions were established according to the limits given by Soriano (1991) and then adapted to administrative district limits (counties) (Viglizzo et al., 2011). Sub region divisions have been done according to vegetation composition and characteristics of soil and climate, but also are related to the nature and intensity of cropping (Hall et al., 1992). In the APR, annual precipitation increases from southwest to northeast (Table 1). Soil silt and clay contents are higher on the Rolling and Southern – E Pampas, while soils are sandier on the west of the APR, on the Southern – W and Central Pampas (Table 2 and Fig. 1). Excluding the Flooding Pampa, where the main land use is the cattle grazing, cropping is at present a regular and predominant land use in the APR. The total area covered was 319,447 km^2.

Climate variables were taken from Bianchi and Cravero (2010) (Table 1) and soil descriptions from INTA (1990) and Salazar et al. (1980) (Table 2). This data was organized in a Geographic Information System (GIS) to estimate the mean values of each sub region (Tables 1 and 2). Surface soil textures representative of each sub

Table 1
Climatic characteristics and climatic region of Argentinean Pampa sub regions.

Sub-region[a]	Temp[a] (°C)	PP[a] (mm)	PET[a] (mm)	Climate region[b]
Central Pampa	16	904	811	WTM
Flooding Pampa	15	980	776	WTM
Rolling Pampa	17	1010	873	WTM
Southern Pampa – E	14	912	738	WTM
Southern Pampa – W	14	766	739	WTM

[a] E: Eastern; W: Western; Temp: mean annual temperature; PP: mean annual precipitation; PET: mean annual potential evapotranspiration.
[b] According to IPCC CAM classification (IPCC, 2006e); WTM: warm temperate, moist.

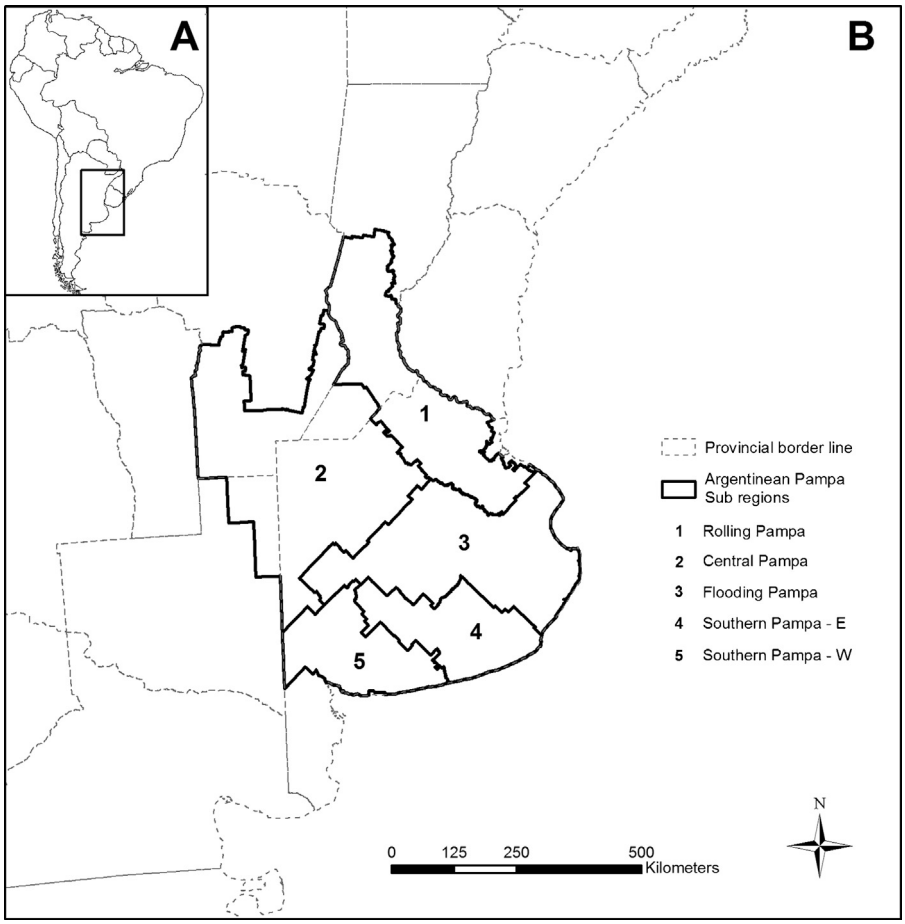

Fig. 1. (A) South America. (B) Sub regions of Argentinean Pampa Region adapted from Soriano (1991). E: Eastern; W: Western.

Table 2
Soil characteristics and soil types of Argentinean Pampa sub regions.

Sub-region[a]	Main soil subgroups[b]	Area (%)	Weighted average size distribution[c] ($g\,kg^{-1}$)			Bulk density[d] ($Mg\,m^{-3}$)		IPCC soil class[e]
			Clay	Silt	Sand	Cropped	Uncropped	
Central Pampa	*Entic Hapludolls*	25	149 (0.3)	273 (0.75)	578 (0.42)	1.48	1.17	HAC
	Entic Haplustolls	23						
	Thaptoargic Hapludolls	10						
	Typic Argiudolls	8						
	Typic Hapludolls	6						
	Others	28						
Flooding Pampa	*Typic Natraquolls*	35	215 (0.19)	330 (0.34)	455 (0.32)	1.30	1.09	HAC
	Thaptoargic Hapludolls	15						
	Entic Hapludolls	10						
	Thaptonatric Hapludolls	10						
	Typic Argiudolls	9						
	Others	21						
Rolling Pampa	*Typic Argiudolls*	51	242 (0.04)	632 (0.02)	126 (0.12)	1.31	1.10	HAC
	Aquic Argiudolls	11						
	Vertic Argiudolls	9						
	Others	29						
Southern Pampa – E	Typic Argiudolls	69	294 (0.2)	307 (0.04)	399 (0.17)	1.21	1.01	HAC
	Typic Natraquolls	8						
	Others	23						
Southern Pampa – W	Typic Argiudolls	42	266 (0.18)	380 (0.03)	354 (0.15)	1.35	1.12	HAC
	Typic Argiustolls	42						
	Typic Haplustolls	14						
	Others	2						

[a] E: Eastern; W: Western.
[b] According to USDA Soil Taxonomy.
[c] Values in parentheses are the coefficients of variation.
[d] Estimated using the pedotransfer functions developed by Hollis et al. (2012).
[e] According IPCC CAM classification (IPCC, 2006e); HAC: soils with high activity clay.

region were calculated through the weighted average of particle size distribution data of soil sub-groups present in them. Then we classified soils and climate according to CAM criteria for each sub region (IPCC, 2006e)

2.2. Land use

We used data from national agricultural censuses (INDEC, 1964, 1991, 2004) and "agricultural statistics" (SIIA, 2013) to determine land uses of 122 counties for the periods 1900–1960, 1960–1988 and 1988–2006.

Land uses were classified into two categories: cropland (CL) and grassland (GL). Cropland included areas under annual crops, annual and perennial pastures and fallow land. Perennial pastures were included into this category since, according to Berhongaray et al. (2013), SOC stocks under perennial pastures did not differ from CL in the APR. Grassland category comprised areas under natural grasslands (native vegetation).

The total surveyed area of the counties varied among censuses (INDEC, 1964, 1991, 2004) and given that one of the CAM requirements is that the total area has to be the same between years under evaluation (IPCC, 2006f), data had to be adapted. Thus, we calculated the average surveyed area of each county in the three censuses, and then this area was multiplied by the proportion of each land use in each year (Eq. (1)).

$$A_{ij} = \left(\frac{A_{1960} + A_{1988} + A_{2002}}{3}\right) \times \mathrm{LU}_{ij} \quad (1)$$

where

j = jth land use: CL or GL;
i = ith census year: 1960, 1988 or 2002;
A_{ij} = area for the ith year under the jth land use;
A_{1960} = surveyed area of managed lands of counties 1960;
A_{1988} = surveyed area of managed lands of counties 1988;
A_{2002} = surveyed area of managed lands of counties 2002;
LU_{ij} = proportion of the jth land use for the ith year.

Since census was not performed for year 2006, data from the census of 2002 (INDEC, 2004) was used instead. Data from census 2002 was corrected with the data from the "agricultural statistics" of 2006 (SIIA, 2013), by assuming that an increase in CL corresponded to a decrease in GL, and vice versa.

The areas under conventional tillage and no-till at county scale were obtained from the national agricultural census corresponding to 2002 (INDEC, 2004). To generate the T2 method, we used information about crop species and crops yield (see Section 2.4.3). Hence, based on "agricultural statistics" data (SIIA, 2013), we estimated the area sown and the average yield for the four main crops of the region: maize (*Zea mays* L.) (M), soybean (*Glycine max* (L.) Merr.) (S), sunflower (*Helianthus annuus* L.) (F) and wheat (*Triticum aestivum* L.) (W). For 1960, the area sown and the average yield of those crops were considered equal to those in 1969 (the first year with records), assuming that agricultural expansion and technology did not change significantly between 1960 and 1969.

2.3. IPCC carbon accounting method Tier 1

The IPCC method estimates changes in SOC stock for the top 30 cm of a soil over an inventory time period. Soil organic C stocks are computed multiplying SOCref stock by change factors and by the area occupied by a particular land use (A_i) (Eq. (2)). Reference SOC represents SOC stock under native vegetation and the change factors are: (1) land-use factor (Flu) that reflects SOC changes associated with the type of land use, (2) management factor (Fmg) representing the main management practice specific to a particular land use (e.g. different tillage practices in CL), and (3) an input factor (Fi) representing different levels of C input into the soil. Each of these factors accounts for the change that occurs during a given number of years (D), which are 20 for the default conditions (T1). This tier assumes that after 20 years from a land use change a new SOC stock equilibrium is reached and that SOC changes occur in a linear fashion. For each time period, SOC is estimated for its first (SOC_1) and last year (SOC_2). Then, SOC change is estimated as the difference in stock between them. This difference is divided by D to calculate the annual SOC change rate (ΔSOC) (Eq. (3)), which is a simplification.

$$\mathrm{SOC}_{it} = \mathrm{SOCref} \times \mathrm{Flu}_i \times \mathrm{Fmg}_i \times \mathrm{Fi}_i \times A_i \quad (2)$$

$$\Delta\mathrm{SOC}_i = \frac{\mathrm{SOC}_{i2} - \mathrm{SOC}_{i1}}{D} \quad (3)$$

where

i: ith county with a particular climate, soil type, land use and management;
t: calendar year in which the information was collected.
SOC: estimated SOC stock, Mg C ha^{-1};
SOCref: reference SOC stock, Mg C ha^{-1};
Flu: stock change factor due to a particular land-use, dimensionless;
Fmg: stock change factor due to the management regime, dimensionless;
Fi: stock change factor due to C input to soil, dimensionless;
A: land area with the same climate, soil type, land use and management over the inventory time period, ha;
ΔSOC: annual change in SOC stock, Mg C ha^{-1} yr^{-1};
SOC_{i1}: SOC stock at the beginning of the inventory time period, Mg C ha^{-1};
SOC_{i2}: SOC stock in the last year of an inventory time period, Mg C ha^{-1};
SOC_{i1} and SOC_{i2} are calculated using Eq. (2);
D: time dependence of stock change factors, yr. If the number of years over the inventory time period is less than 20, D = 20. If the number of years over the inventory time period is higher than 20, D = number of years over the inventory time period (IPCC, 2006d).

We used T1 method with default change factors (IPCC, 2006d) to estimate SOC change for the period 1960–2006. No-till management was introduced in the 1990s, and subsequently it was increasingly adopted by farmers. Cropland area under no-till in Argentina grew from almost 0% in the 1980s to approximately 70% in 2006 (AAPRESID, 2012). Therefore, the Fmg for conventional tillage (Fmg = 1) was assigned for 1960 and 1988. For 2006, first we applied Eq. (2) for conventional tillage (Fmg = 1) and then we multiplied this result by percentage area under this management. Second, we applied Eq. (2) for no-till (Fmg = 1.15) and then we multiplied this result by percentage area under this management. Finally, both results were summed obtaining a single value of SOC by county. The Fi was set at medium inputs, because CAM considered this category as "representative for annual cropping with cereals where all crop residues are returned to the field" (IPCC, 2006d), given the APR management systems fit into this description. For CL, the IPCC default Flu was 0.69 for all sub regions since all fall within the same soil and climate IPCC category (Tables 1 and 2).

2.4. IPCC carbon accounting method improved (Tier 2)

2.4.1. Reference SOC stock

Reference SOC stock of each sub region was obtained from local literature (Table 3). We selected articles in which SOC under

Table 3
Soil organic carbon contents under native vegetation in the different sub regions of the Argentinean Pampa Region.

Sub region[a]	Study[b]	T2 SOCref[c] ($Mg_{(0–20\,cm)}\,ha^{-1}$)	T2 SOCref[c] ($Mg_{(0–30\,cm)}\,ha^{-1}$)	T1 SOCref[d] ($Mg_{(0–30\,cm)}\,ha^{-1}$)
Central Pampa	Quiroga et al., 2001$_{(25)}$	55	68	
Central Pampa	Vázquez et al., 1990$_{(20)}$	51	63	
Central Pampa	Average	54	66	88
Flooding Pampa	Lavado et al., 1996$_{(15)}$	58	72	
Flooding Pampa	Average	58	72	88
Rolling Pampa	Andriulo et al., 2012$_{(30)}$	66	82	
Rolling Pampa	Cantú et al., 2007$_{(20)}$	58	72	
Rolling Pampa	Ferreras et al., 2001$_{(20)}$	64	79	
Rolling Pampa	Michelena et al., 1988$_{(20)}$	62	77	
Rolling Pampa	Vázquez et al., 1990$_{(20)}$	58	72	
Rolling Pampa	Average	62	77	88
Southern Pampa – E	Andriulo et al., 2012$_{(30)}$	98	122	
Southern Pampa – E	Roldán, 2012$_{(20)}$	88	110	
Southern Pampa – E	Vázquez et al., 1990$_{(20)}$	71	89	
Southern Pampa – E	Average	86	107	88
Southern Pampa – W	Blanco et al., 2005$_{(12)}$	50	62	
Southern Pampa – W	Roldán, 2012$_{(20)}$	57	71	
Southern Pampa – W	Average	54	66	88

[a] E: Eastern; W: Western.
[b] The numbers between parentheses indicate the depth reported by the authors.
[c] Estimations of reference soil organic carbon (SOCref) stocks at different depths for Tier 2 (T2) were performed using SOC stocks reported by the authors and the model proposed by Bernoux et al. (1998) (Eq. (7)).
[d] A nominal error estimate of ±90% (expressed as 2× standard deviations as percent of the mean) was assumed with Tier 1 (T1).

pristine or semi-pristine condition had been evaluated. Then, we averaged the values for each sub region. For the standardization of soil sampling depth we used a potential model (Bernoux et al., 1998) (Eq. (4)) where the accumulated C (Ac) is a function of the depth (d), of a parameter (A) which represents the amount of C accumulated to the top 1 m soil depth, and another parameter (B) that describes the curvature of the function.

$$Ac = A \times d^B \tag{4}$$

where

Ac: SOC at a certain depth, $Mg\,C\,ha^{-1}$;
A: SOC stock for the top 1 m soil depth, $Mg\,C\,ha^{-1}$;
d: soil depth, m;
B: describes the curvature of the function, dimensionless.

We used the B parameter estimated by Berhongaray et al. (2013) for different land uses in the APR (0.57 for CL and 0.53 for uncropped situations). Due to the lack of bulk density information and the need of converting SOC concentration values into SOC stock values, we estimated bulk density from particle size distribution and SOC content for cultivated and non cultivated soils (Hollis et al., 2012) at county scale. Then, we calculated the bulk density average of each sub region (weighting by county area) (Table 2) and these results were very similar and therefore highly correlated ($r = 0.84$) with the bulk density measured and reported by other authors (Mon et al., 1986; Taboada and Lavado, 1988; Hein et al., 1989; Chagas et al., 1994; Krüger, 1996; Díaz-Zorita and Basanta, 1999; Sasal et al., 2000; Studdert and Echeverría, 2002; Díaz-Zorita et al., 2004; Álvarez and Barraco, 2005; Álvarez et al., 2006; Ferreras et al., 2007; Maurette et al., 2012) for the different APR sub regions.

2.4.2. General equation

According to IPCC's *2006 Guidelines for National Greenhouse Gas Inventories* (IPCC, 2006c), deriving SOC change factors using local data is deemed good practice. However, in order to improve the CAM we did not derive the same factors used in T1 method. We have developed a CL factor (Fc), a GL factor (Fg) and a management factor for CL (Fmg_2). Then, instead of using Eq. (2), where change factors are applied to the SOCref, we used Eq. (5) where the factors are applied to an initial SOC storage (SOCi), which could be or not SOCref:

$$SOC_{it} = SOCi_i \times (Fc\,or\,Fg)_i \times Fmg_{2i} \times A_i \tag{5}$$

where

i: ith county with a particular climate, soil type, land use and management;
t: calendar year in which the information was collected;
SOC: estimated SOC stock, $Mg\,C\,ha^{-1}$;
$SOCi_i$: initial SOC stock (this is the SOCref for the GL converted to CL category, or the SOC stock reached in CL in the previous inventory year for the CL remaining CL category or CL converted to GL), $Mg\,C\,ha^{-1}$;
Fc: stock change factor of T2 for croplands, dimensionless;
Fg: stock change factor of T2 for grasslands, dimensionless;
Fmg_2: stock change factor of T2 for management regime, dimensionless;
A: land area with the same climate, soil type, land use and management over the inventory time period, ha.

2.4.3. Stock change for croplands (Fc) and grasslands (Fg)

Our aim was to develop regression models to estimate SOC stock change factors using easily obtainable data as predictors. We generated many hypothetic situations with available census data. Then, we obtained the data necessary to run many simulations with the version 26.3 of RothC (Coleman and Jenkinson, 1999) to simulate SOC stock changes for all those hypothetic situations. Finally, we fitted regression models of these SOC stock changes on census variables to estimate Fc and Fg.

RothC is a model for SOC change simulation in different soils and under different climates, but it has been created to simulate SOC changes only under tillage conditions. Hence, soil management with tillage has been assumed as our reference condition and then we applied the Fmg_2 to estimate SOC stocks under no-till (see Section 2.4.4). For Fc and Fg, simulations were run for the top 20 cm of soil and for five periods: 10, 20, 30, 40 and 50 yr. Soil depth was set at 20 cm because we wanted to make comparable the estimated with the observed values available (see Section 2.5).

For Fc we simulated SOC changes under twenty different crop rotations, in order to cover a wide range of situations. The simulations ranged from monoculture of W, M, S and F to rotations

composed by these four crops and perennial pastures, with a 1:1 ratio between crops and perennial pastures. For crop yields we defined three yield levels for each crop: low, medium and high (see Supplementary Material available with this article online). These yield levels corresponded, respectively, to the minimum, average and maximum county average yield registered for the whole APR (SIIA, 2013). In order to estimate the yield and crop effect, we assigned a yield level at random to the crop/s in each rotation. Thus, all rotations were simulated three times, each one with a different combination of crop yield levels. Carbon input used in the CL simulations was obtained from crop yields. The aboveground dry matter production was estimated assuming average harvest indexes of 0.45, 0.40, 0.35, and 0.45 for W, S, F, and M, respectively (Studdert and Echeverría, 2000). The belowground C input (roots + rhizodeposition) was calculated assuming root:aboveground biomass ratios of 0.48, 0.38, 0.38, and 0.35 for W, S, F, and M, respectively (Buyanovsky and Wagner, 1997), and the proportion of roots in the top 20 cm of the soil of 0.90, 0.84, 0.84, and 0.91, respectively (Domínguez and Studdert, 2006, based on Buyanovsky and Wagner, 1997). In all cases, C content of the estimated biomass was assumed as 43% (Sánchez et al., 1996).

The starting points of CL simulations were the SOCref's of each sub region (see Section 2.4.1). We calculated the change ratios through the comparison of the SOC stock reached at a given time with the corresponding to the end of the previous one (either SOCref at the starting point or the final SOC stock of the previous simulation period). Doing this for all possible combinations among SOCref, SOC stocks at 10, 20, 30, 40, and 50 yr, for all crop rotations, crop yield levels and sub regions, gave rise to 4500 SOC change ratios. Finally, in order to obtain a simpler way to calculate the SOC stock change ratios (Fc), we fitted a second order linear model based on census data used to obtain RothC outputs (Eq. (6)).

$$\mathrm{Fc} = \mathrm{Intercept} + \mathrm{SOCi} + \mathrm{SOCi}^2 + \mathrm{Mp} + \mathrm{Mp}^2 + \mathrm{Sp} + \mathrm{Sp}^2 + \mathrm{Fp} + \mathrm{Fp}^2 + \mathrm{Wp} + \mathrm{Wp}^2 + Y + Y^2 + T + T^2 + \mathrm{SR_{Fl}} + \mathrm{SR_{Ro}} + \mathrm{SR_{Se}} + \mathrm{SR_{Sw}} + \mathrm{PP} \quad (6)$$

where

SOCi: initial SOC storage;
Mp: time proportion of the rotation with M;
Sp: time proportion of the rotation with S;
Fp: time proportion of the rotation with F;
Wp: time proportion of the rotation with W;
Y: average yield (*Y*) of each crop weighted by the proportion of each one in the rotation;
PP: time proportion of the rotation with perennial pastures (this variable had only two levels: 0% and 50%);
T: time in years (which should not be less than 10 years, given this was the minimum time period used in RothC simulations);
$\mathrm{SR_{Fl}}$, $\mathrm{SR_{Ro}}$, $\mathrm{SR_{Se}}$, $\mathrm{SR_{Sw}}$: are the Argentinean Pampa Sub regions. For Flooding Pampa $\mathrm{SR_{Fl}} = 1$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$; for Rolling Pampa $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 1$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$; for Southern Pampa – Eastern $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 1$ and $\mathrm{SR_{Sw}} = 0$; for Southern Pampa – Western $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 1$ and for Central Pampa $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$.

For the Fg we simulated SOC changes under GL condition. Carbon inputs under GL were estimated using the "inverse mode" of RothC (Coleman and Jenkinson, 1999) and the SOCref of each sub region. The starting points of GL simulations were taken from the results of CL simulations for each sub region. In order to cover a wide range of SOCi, we selected minimum, maximum and the intermediate SOC values (see Supplementary Material available with this article online). We run the GL simulation for 10, 20, 30, 40 and 50 yr and using the same procedure as for Fc, we compared the SOC achieved in the different periods and calculated the SOC stock changes. With all the possible combinations we generated 150 SOC change ratios. Finally, Fg derivation was also done by fitting a second order linear model (Eq. (7)).

$$\mathrm{Fg} = \mathrm{Intercept} + \mathrm{SOCi} + \mathrm{SOCi}^2 + T + T^2 + \mathrm{SR_{Fl}} + \mathrm{SR_{Ro}} + \mathrm{SR_{Se}} + \mathrm{SR_{Sw}} \quad (7)$$

where

SOCi: initial SOC storage;
T: time in years (which should not be less than 10 years, given this was the minimum time period used in RothC simulations);
$\mathrm{SR_{Fl}}$, $\mathrm{SR_{Ro}}$, $\mathrm{SR_{Se}}$, $\mathrm{SR_{Sw}}$: are the Argentinean Pampa Sub regions. For Flooding Pampa $\mathrm{SR_{Fl}} = 1$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$; for Rolling Pampa $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 1$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$; for Southern Pampa – Eastern $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 1$ and $\mathrm{SR_{Sw}} = 0$; for Southern Pampa – Western $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 1$ and for Central Pampa $\mathrm{SR_{Fl}} = 0$, $\mathrm{SR_{Ro}} = 0$, $\mathrm{SR_{Se}} = 0$ and $\mathrm{SR_{Sw}} = 0$.

For both factors the final model was selected by applying a stepwise procedure.

2.4.4. Management stock change factor ($\mathrm{Fmg_2}$)

For the conventional tillage the $\mathrm{Fmg_2}$ was equal to the Fmg of T1 ($\mathrm{Fmg} = \mathrm{Fmg_2} = 1$), because RothC simulate SOC changes under tillage conditions.

The $\mathrm{Fmg_2}$ for no-till was derived using the information of a meta-analysis carried out by Steinbach and Alvarez (2006) of SOC change due to the introduction of no-till in the APR. In order to estimate the potential of no-till to mitigate the global warming effect they developed a model (Eq. (8)) to predict SOC under no-till ($\mathrm{SOC_{NT}}$) using SOC under tillage systems ($\mathrm{SOC_T}$) as an independent variable, for the upper 20 cm of soil profiles (Eq. (8), $R^2 = 0.94$).

$$\mathrm{SOC_{NT}} = 0.98\mathrm{SOC_T} + 5.5 \quad (8)$$

where

$\mathrm{SOC_{NT}}$: SOC under no-till, Mg C ha^{-1};

$\mathrm{SOC_T}$: SOC under tillage system, Mg C ha^{-1}.

The SOC under tillage was obtained from the SOC stock reached in CL in 2006 using Eq. (5) with the $\mathrm{Fmg_2}$ for conventional tillage. Then, in order to derive the $\mathrm{Fmg_2}$ for no-till management we divided the $\mathrm{SOC_{NT}}$ calculated from Eq. (8) by the SOC under tillage (Eq. (9)).

$$\mathrm{Fmg_{2NT}} = \left(\frac{\mathrm{SOC_{NTi}}}{\mathrm{SOC_{Ti}}}\right) \quad (9)$$

where:

i: *i*th county;
$\mathrm{Fmg_{2NT}}$: management stock change factor of T2 for no till;
$\mathrm{SOC_{NT}}$: SOC under no-till, Mg C ha^{-1};
$\mathrm{SOC_T}$: SOC under tillage system, Mg C ha^{-1}.

Despite a proper comparison between management systems should be performed using the equivalent soil mass procedure (VandenBygaart and Angers, 2006) the methodology proposed by the IPCC is based on fixed depth approach. Therefore, $\mathrm{Fmg_2}$ was derived using the fixed depth approach. Because of this, it is likely that both methods (T1 and T2) overestimate no-till effect (VandenBygaart and Angers, 2006).

2.4.5. Application of T2 method in the Argentinean Pampa Region (APR)

The expansion of agriculture in the APR became important in the early 20th century (Hall et al., 1992). Therefore, we started the simulations in 1900. Although there is no empirical data, many authors describe the main rotation of the APR from early centuries until the 1990s with a 1:1 ratio between crops and pastures (Soriano, 1991; Hall et al., 1992; Bernardos et al., 2001; Paruelo et al., 2006). However, during the last decades farmers tended to replace pasture-crop rotations by continuous cropping, mainly due to economic reasons (Satorre, 2005; Paruelo et al., 2006; Manuel-Navarrete et al., 2007). Since national agricultural censuses (INDEC, 1964, 1991, 2004) and "agricultural statistics" (SIIA, 2013) do not provide information about rotation compositions, we assumed that the whole region, with the exception of the Flooding Pampa, had been under pasture-crop rotations until 1988 and that later on, land use changed to continuous cropping. The Flooding Pampa was excluded from this assumption, because in 2006 it still presented low cropping intensity.

Given we used census information to determine land uses, we only had the "picture" for the three census years, but we do not know exactly the time when a GL was converted to a CL, or vice versa, between two consecutive censuses. For the periods 1969–1988 and 1988–2006, the rates of increase of CL in the whole APR were approximately constant (SIIA, 2013). In order to define the T of a new CL or GL, we assumed a constant rate of land use change. Thus, the average T of a new land use was calculated as the difference between years divided by two. For example, if in 1988 there had been 100 ha of CL and in 2006 this surface had increased up to 120 ha, the new 20 ha converted to CL are 9 years old (T = (2006–1988)/2) within the period (T). The other 100 ha was included into the category "CL remaining CL" with 18 years old (T = 2006–1988) within the period (T). In this last category we used the SOC estimated in the previous period as the SOCi to estimate the Fc. The same procedure was used to estimate the T for the Fg.

The Fmg_2 for conventional tillage was assigned for 1960 and 1988. For 2006, first we applied Eq. (5) for conventional tillage ($Fmg_2 = 1$) and then we multiplied this result by percentage area under this management. Second, we applied Eq. (5) for no-till (Fmg_{2NT}) and then we multiplied this result by percentage area under this management. Finally, both results were summed obtaining a single value of SOC by county.

2.5. CAM evaluation

Mean SOC value for each county was estimated by the average of the observed SOC values obtained from Sainz Rozas et al. (2011). These authors collected SOC data from recognized soil laboratories either private or of experiment stations of the National Institute of Agricultural Technology. They collected 31,619 samples from the 0–20 cm layer of production fields during 2005 and 2006. Since our study area is smaller than that surveyed by Sainz Rozas et al. (2011), we used the results of 25,306 samples. We integrated SOC averages at a county scale and also we calculated the number of samples per area unit (10 km^2) for each county, and referred this to as sampling density. Besides, observed averages (Sainz Rozas et al., 2011), T1 and T2 estimated values were aggregated through weighted averages by area to pass from the county to the sub region scale.

In order to make comparable T1 method estimations with the observed averages, the T1 method values were corrected to the upper 20 cm of soil through Eq. (4). Since grassland or pasture fertilization is not a common practice in the study region, we assumed that all soil samples submitted by farmers to the laboratories proceeded from CL and, hence, we used the SOC stocks estimated for CL with T1 and T2 methods to evaluate their matching with the observed averages.

Carbon accounting method performance was evaluated with several statistic tools. Simple least square linear regression analyses of observed averages on both T1 and T2 methods estimated values were performed at county and sub region scales. Moreover, the equality of the intercept (β_0) and of the slope (β_1) of the regression line to 0 and 1, respectively, was tested through 95% confidence intervals.

From observed data (Sainz Rozas et al., 2011), a 95% prediction interval for a new observation was calculated for each county. The proportion of counties in which the T1 or T2 methods estimated values fell within the intervals was used as a measure of the quality of the estimations. We also calculated the difference between observed average and T1 and T2 methods estimated values, from now on referred to as bias error (BE) (although it is not the classical definition for an estimator of BE). Then, we also studied the relation of this statistic with sampling density.

We also run T1 and T2 methods using input data generated in two long term experiments carried out in the experiment station of the *Unidad Integrada Balcarce* (Balcarce, Buenos Aires Province, Argentina, 37°45′S, 58°18′W, Southeastern Pampa – E). Then, we validated model outputs against SOC data from those experiments. Both experiments were carried out on a complex of fine, mixed, thermic Typic Argiudoll (Mar del Plata series, INTA, 1979) and fine, illitic, thermic Petrocalcic Paleudoll (Balcarce series, petrocalcic horizon below 0.7 m, INTA, 1979). One of the experiments, called "Crop-pasture Rotation Experiment" was conducted under conventional tillage (moldboard plowing, disking, and field cultivation/spike harrowing) with a first phase between 1976 and 1993 (Studdert et al., 1997) and a second one between 1994 and 2005 (Eiza et al., 2006). For this study, it was used the information from four rotations between 1993 and 2005. Two of the rotations included continuous cropping with the sequence M-S-W for 12 yr, one under conventional tillage and the other under no-till. The two other rotations included 3 yr under PP and 3 yr under M-S-W, repeated twice (12 yr), one of them under conventional tillage and the other under no-till. All crop rotation treatments were also under two nitrogen (N) fertilization levels: control without N and fertilization with 120 kg N ha^{-1} to all grain crops.

The second experiment called "Continuous Cropping Experiment", was conducted under conventional tillage between 1984 and 1996 (Studdert and Echeverría, 2000). This experiment had 16 crop sequences including W, S, F, and M and two levels of N fertilization (the same mentioned for the "Crop-pasture Rotation Experiment") on W and M.

3. Results and discussion

3.1. Tier 1 vs. Tier 2

In order to apply reference C stocks and stock change factors, soils and climate of the entire planet are classified by the IPCC's CAM within seven soil types, one of which is organic and the others are mineral soil types and twelve climate regions (IPCC, 2006e). When running T1 method, the whole APR resulted included within the same climate region (Table 1) and with the same soil type (Table 2). Therefore, with T1 method, the whole APR showed the same estimated SOCref (88 Mg ha^{-1}, Table 3). Despite the SOCref average for the whole APR with T2 method (80 Mg ha^{-1}) was quite similar to that resulting for T1 method (88 Mg ha^{-1}, Table 3), literature indicates that SOCref was very different among sub regions (Table 3). Hence, the coarse classification done for T1 method masks a very wide range of environmental conditions and T2 method gained in

Table 4
Models to estimate stock change factors for Tier 2.

Stock change factor	Coefficients[a]	Estimate	Standard error	p-Value
Cropland factor (Fc) ($R^2_{adjusted} = 0.88$)	Intercept	1.119	0.01193	<0.000001
	T	−0.005661	0.0002497	<0.000001
	T^2	0.00002297	0.000004525	<0.000001
	SOCi	−0.008459	0.0003773	<0.000001
	$SOCi^2$	0.00002102	0.000003208	<0.000001
	PP	0.1966	0.006904	<0.000001
	SR_{Fl}	0.03191	0.002192	<0.000001
	SR_{Sw}	0.1312	0.002234	<0.000001
	SR_{Ro}	0.05335	0.002298	<0.000001
	SR_{Se}	0.18170	0.003632	<0.000001
	Wp	−0.0931	0.00679	<0.000001
	Mp	−0.1214	0.01238	<0.000001
	Mp^2	0.1041	0.009358	<0.000001
	Sp^2	−0.06875	0.006672	<0.000001
	Fp^2	−0.04582	0.006896	<0.000001
	Y	0.04937	0.001105	<0.000001
	Y^2	−0.001135	0.0001168	<0.000001
Grassland factor (Fg) ($R^2_{adjusted} = 0.93$)	Intercept	2.499	0.05199	<0.000001
	SOCi	−0.04806	0.002313	<0.000001
	$SOCi^2$	0.0003074	0.00002489	<0.000001
	T	0.00485	0.0003661	<0.000001
	SR_{Fl}	0.07079	0.01651	<0.0001
	SR_{Sw}	−0.02787	0.01706	0.105
	SR_{Ro}	0.117	0.01675	<0.000001
	SR_{Se}	0.348	0.02073	<0.000001

[a] T: time; SOC_i: initial SOC; PP: time proportion of the rotation with perennial pastures; Wp: time proportion with wheat; Mp: time proportion with maize; Sp: time proportion with soya; Fp: time proportion with sunflower; Y: average yield; SR_{Fl}, SR_{Ro}, SR_{Se}, SR_{Sw}: are the Argentinean Pampa Sub regions. For Flooding Pampa $SR_{Fl} = 1$, $SR_{Ro} = 0$, $SR_{Se} = 0$, $SR_{Sw} = 0$; for Rolling Pampa $SR_{Fl} = 0$, $SR_{Ro} = 1$, $SR_{Se} = 0$, $SR_{Sw} = 0$; for Southern Pampa – Eastern $SR_{Fl} = 0$, $SR_{Ro} = 0$, $SR_{Se} = 1$, $SR_{Sw} = 0$; for Southern Pampa – Western $SR_{Fl} = 0$, $SR_{Ro} = 0$, $SR_{Se} = 0$, $SR_{Sw} = 1$ and for Central Pampa $SR_{Fl} = 0$, $SR_{Ro} = 0$, $SR_{Se} = 0$, $SR_{Sw} = 0$.

accuracy by assigning different SOCref to the sub regions (Batjes, 2011).

Final models for Fc and Fg were highly significant ($p < 0.0001$) and presented a high determination coefficient (Table 4). Therefore, both models adequately described the hypothetic SOC changes generated with RothC simulations and can be used to estimated Fc and Fg as function of cropping and site variables.

When using T1 method to estimate SOC stock for "GL converted to a CL" category, in the APR and under conventional tillage, Fmg and Fi are equal to 1. Hence, after twenty years from land use change, T1 method estimation is merely the SOCref multiplied by the Flu (0.69, IPCC, 2006d) (Eq. (2)). Despite Fc estimates are for the upper 20 cm and Flu estimates are for the upper 30 cm of soil, Fc for "GL converted to CL" varied among sub regions and periods, but individually never reached a value as low as 0.69 (Flu, IPCC, 2006d) (Table 6). However, since T2 method uses an Fc for the "CL remaining CL" category, SOC continues decreasing through the time periods considered and therefore, SOC stocks of CL estimated with T2 method for 2006 were less than 69% of SOCref (T1) for all sub regions (results not shown).

The Flu represents the average loss of C in 20 years and assumes linear change until reaching the new equilibrium (assumed to occur 20 years after land use change). This is a great over simplification since it has been demonstrated that the rate of SOC loss is greater initially and then diminishes over time. On the other hand, the period to reach a new equilibrium after a land use change could be highly variable according to soil type and management practices applied (Dalal and Mayer, 1986; Senthilkumar et al., 2009). In contrast, T2 method assumes that for CL, SOC is continuously changing with time which is much more realistic. Another consideration respect to Flu is that when T1 method has to account for the return of CL to GL, it is assumed that the accumulation of SOC is a process symmetrical to SOC loss. It is well known that SOC is more rapidly lost than gained (Jastrow et al., 1996; Six et al., 2000; Smith, 2004) and therefore, that assumption introduces uncertainty to SOC gain estimation under GL after CL.

The values of the Fmg and Fi factors arise from qualitative categories for different management activities in CL. The Fi has three categories (low, medium and high input) (IPCC, 2006d) and given these categories do not depend of objective values, sometimes it is difficult and subjective to assign the Fi to a cropland system.

Tier 1 is based on many implicit assumptions which are not entirely consistent with the current scientific understanding of C cycling in soils (Sanderman and Baldock, 2010) and such conceptual constrains/limitations have to be avoided through proposing adequate T2 method. Instead of using empirical data to derive T2 factors, we simulated SOC changes under many conditions and fitted models to derive the stocks change factors. Therefore, the effects of time, soil, climate, cropping system, crop yields, and initial SOC stock are incorporated in the obtained stock change factors for T2 method (Table 4). On the other hand, our T2 method used Fg when land use changed from CL to GL, but If the conversion was from GL to CL, Fc was applied. Therefore, T2 method did not assume equal gain and loss rates of SOC stock.

Table 5
Confidence intervals for the parameters of the regression line of observed on estimated values (β_0 and β_1) at county and sub-region scale for T1 and T2.

	County scale				Sub-region scale		
	β_0	β_1	p-Value	Proportion[a]	β_0	β_1	p-Value
T1	(54.5; 220.7)	(−3.3; −0.2)	0.03	0.46	–	–	0.35
T2	(−19.5; 3.7)	(1.1; 1.7)	<0.001	0.87	(−54.6; 30.4)	(0.5; 2.5)	0.02

[a] Proportion of counties in which the estimated value of T1 or T2 fell in a 95% prediction interval for a new observation calculated from observed values.

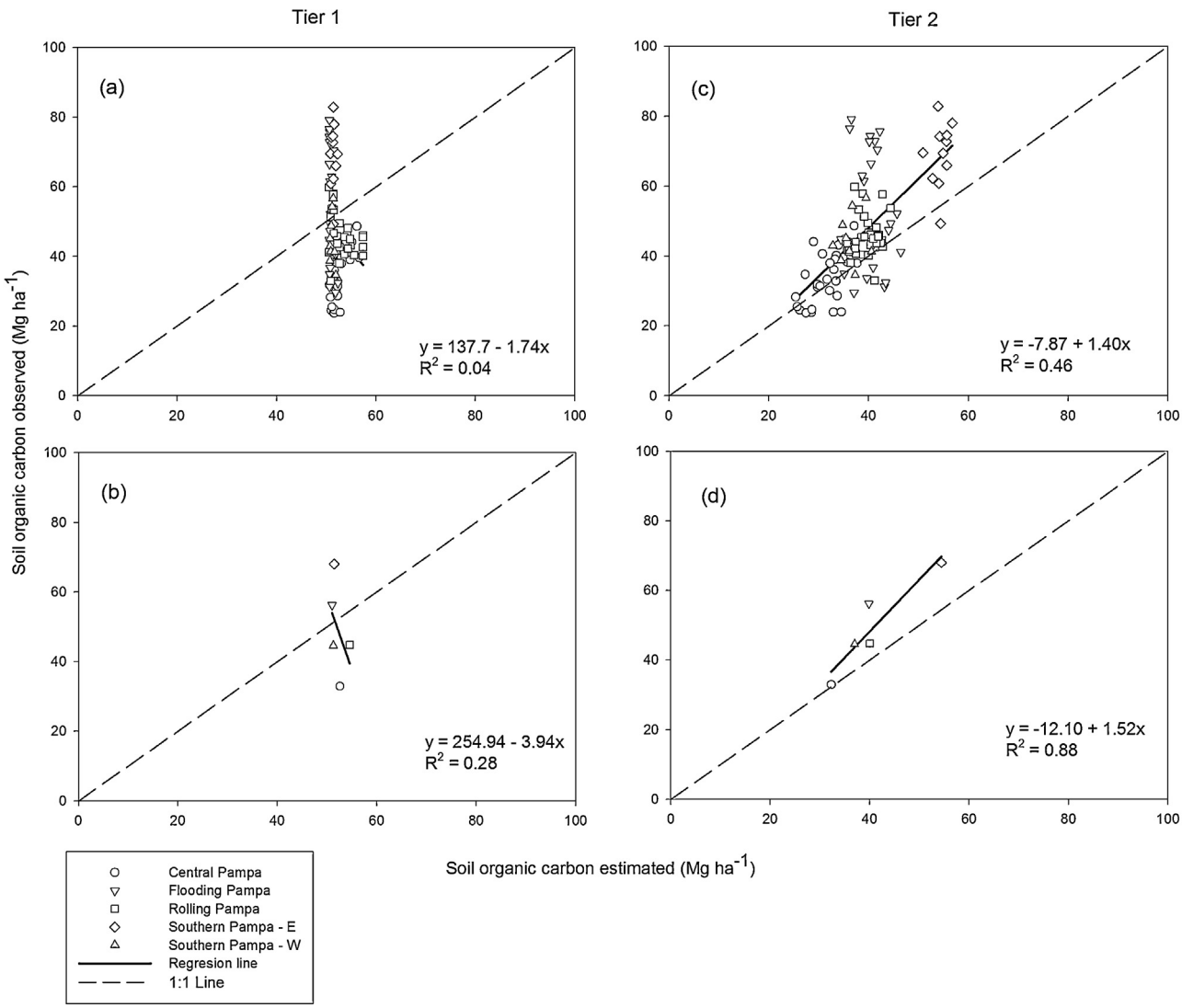

Fig. 2. Soil organic carbon stocks observed and estimated with Tier 1 (a, b) and Tier 2 (c, d) at different scales (county (a, c) and sub-region (b, d) scales). E: eastern; W: western.

3.2. CAM tier evaluations

At county scale, the regression line of observed averages on estimated values with T1 method showed a very low determination coefficient ($R^2 = 0.04$) (Fig. 2a), which grew approximately twelve times when T2 method was used ($R^2 = 0.46$) (Fig. 2c). When we aggregated the results at the sub region scale, there was not significant linear relationship between observed and T1 estimated averages ($p = 0.35$, Table 5, Fig. 2b), but with T2 method the regression line was significant ($p = 0.02$, Table 5, Fig. 2d) and with high determination coefficient ($R^2 = 0.88$).

At county scale, the confidence intervals for β_0 and β_1 with T1 method did not contain 0 and 1, respectively (Table 5). With T2 method, the confidence interval for β_0 and β_1 contained 0 and 1, respectively, at sub region scale, but confidence interval for β_1 did not contain 1 at county scale (Table 5). Besides, the improvement using T2 method can also be seen in the proportion of counties which fell within the prediction interval for a new observation. That proportion was 0.46 using T1 method and increased to 0.87 using T2 method (Table 5). Hence, these results show a poor performance of T1 method and an important improvement with T2 method to estimate SOC stocks associated to land use for agriculture.

Observed county SOC stocks were calculated through averaging the data provided by Sainz Rozas et al. (2011) and the estimated ones were calculated with T2 method. Therefore, both estimates have their own sources of error. The observed values had two

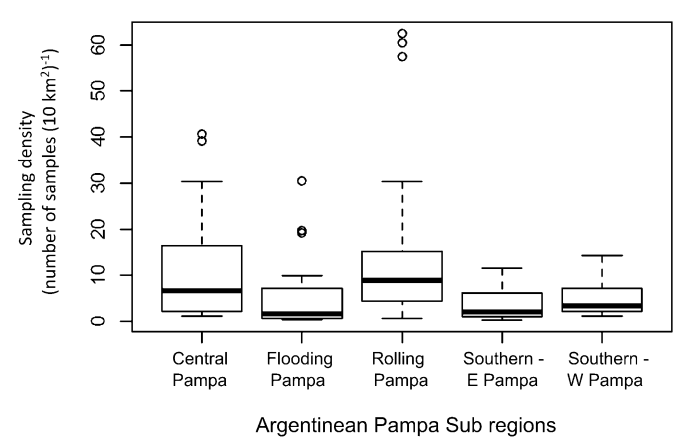

Fig. 3. Sampling density across Argentinean Pampas Sub regions. E: Eastern, W: Western.

Table 6
Land use change factors of Tier 2, for cropland remaining cropland (CL to CL), grassland converted to cropland (GL to CL), grassland remaining grassland (GL to GL), and cropland converted to grassland (CL to GL), at different time periods.

Sub region	Period	Land use change factors of Tier 2 (T2)				Fmg_2
		CL to CL (Fc)	GL to CL (Fc)	GL to GL (Fg)	CL to GL (Fg)	
Central Pampa	1900–1960	–	0.73 ± 0.01[a]	–	–	–
	1960–1988	0.84 ± 0.00	0.81 ± 0.01	1.00 ± 0.00	1.19 ± 0.01	–
	1988–2006	0.84 ± 0.01	0.76 ± 0.01	1.00 ± 0.00	1.31 ± 0.02	1.04 ± 0.01
Flooding Pampa	1900–1960	–	0.75 ± 0.01	–	–	–
	1960–1988	0.85 ± 0.00	0.81 ± 0.00	1.00 ± 0.00	1.16 ± 0.01	–
	1988–2006	0.96 ± 0.01	0.88 ± 0.01	1.00 ± 0.00	1.22 ± 0.03	1.01 ± 0.00
Rolling Pampa	1900–1960	–	0.77 ± 0.01	–	–	–
	1960–1988	0.86 ± 0.00	0.83 ± 0.00	1.00 ± 0.00	1.12 ± 0.01	–
	1988–2006	0.83 ± 0.01	0.76 ± 0.01	1.00 ± 0.00	1.20 ± 0.02	1.04 ± 0.01
Southern Pampa – E[b]	1900–1960	–	0.75 ± 0.01	–	–	–
	1960–1988	0.86 ± 0.00	0.80 ± 0.00	1.00 ± 0.00	1.11 ± 0.01	–
	1988–2006	0.83 ± 0.01	0.73 ± 0.01	1.00 ± 0.00	1.15 ± 0.02	1.01 ± 0.00
Southern Pampa – W[b]	1900–1960	–	0.85 ± 0.01	–	–	–
	1960–1988	0.90 ± 0.01	0.91 ± 0.01	1.00 ± 0.00	1.01 ± 0.01	–
	1988–2006	0.85 ± 0.01	0.82 ± 0.02	1.00 ± 0.00	1.08 ± 0.02	1.01 ± 0.00
Whole region	1900–1960	–	0.76 ± 0.01	–	–	–
	1960–1988	0.86 ± 0.00	0.83 ± 0.01	1.00 ± 0.00	1.14 ± 0.01	–
	1988–2006	0.86 ± 0.01	0.79 ± 0.01	1.00 ± 0.00	1.22 ± 0.02	1.03 ± 0.01

[a] Mean ± 95% confidence limits.
[b] E: Eastern, W: Western.

important limitations. First, these values were not chosen through a random procedure but came from farmers who collected and sent samples to the surveyed laboratories. Even though this mechanism granted a high number of cases, we only represented farmers who are somehow used to taking soil samples, and it is likely that those farmers were associated to better soil management practices. Thus, because we did not represent farmers who do not take soil samples, our observed values could be representing a biased (overestimated) view of the reality. Second, sampling density was very different among counties and sub regions (Fig. 3), causing uncertainty where it was very low. This is supported by Fig. 4 where it can be seen that BE variation among counties tends to decrease (particularly using T2 method) with sampling density.

Regarding the error associated to T2 method estimates, the quality of model inputs is an important issue. The "agricultural statistics" (SIIA, 2013) provides a valuable information that has been used in several studies to analyze trends and patterns of land uses (e.g. Viglizzo and Frank, 2006; Manuel-Navarrete et al., 2007; Viglizzo et al., 2011; Carreño et al., 2012). However, this information is not entirely consistent with National Agricultural Census (INDEC) information (Paruelo et al., 2004) and this uncertainty introduced by the differential characteristics of information sources is unfailingly transferred to T2 method estimations.

In order to re-check T1 and T2 methods performance given the limitations of model input information and of the observed values at county/sub region scale, we also evaluated them against data from long-term experiments (field scale). These experiments have accurate records about rotation composition, crop yields, land use time and SOC stocks. The performance of T1 method at field scale (Fig. 5a) was as poor as that shown for county (Fig. 2a) and sub region (Fig. 2b) scales. This is not surprising because neither T1 method nor T2 method were designed to apply at field scale.

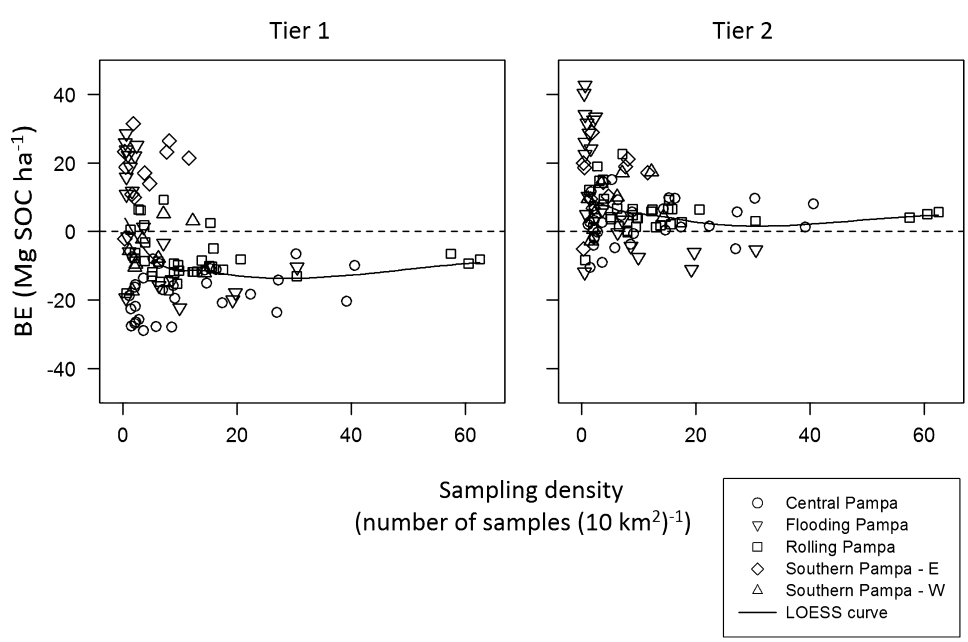

Fig. 4. Bias error (BE) in response to the sampling density. E: Eastern, W: Western. LOESS curve is a local regression (Cleveland and Loader, 1996).

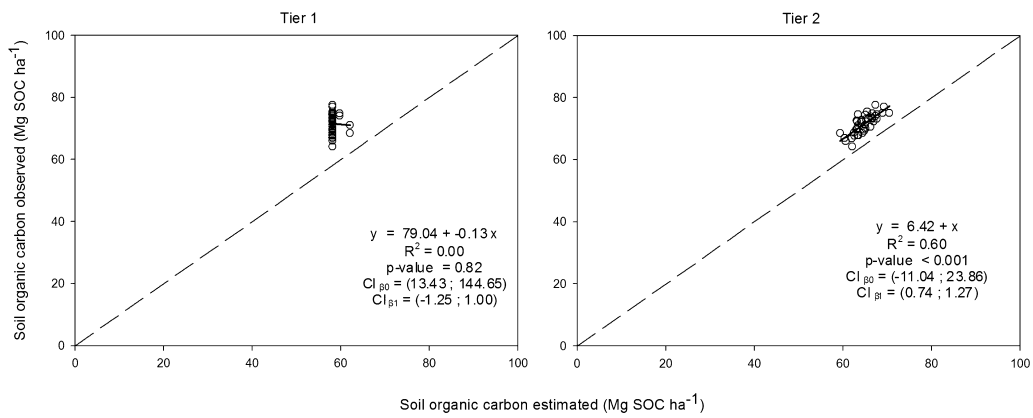

Fig. 5. Soil organic carbon stocks observed in long term experiments and estimated with Tier 1 approach and Tier 2 approach, at field scale.

However, the determination coefficient ($R^2 = 0.60$), the significance of the regression line and the fact that confidence interval for β_0 and β_1 contained 0 and 1, respectively (Fig. 5b), indicates that T2 method estimates had a good association with the observed values at field scale. Therefore, T2 method estimations were improved by increasing the information quality of model inputs.

Tier 2 can be used with different degrees of uncertainty depending on the spatial scale. At sub region scale the estimations were very good (Fig. 2d). The average SOC observed on the three sub regions with higher sampling density (Rolling Pampa, Southern Pampa – W and Central Pampa) were very similar than the SOC estimated with T2 method (Fig. 2d). Soil organic C estimates with T2 method in the other two sub regions, Flooding Pampa and Southern Pampa – E, were 11.7% and 8.6% lower, respectively, than the observed averages.

At county scale, T2 method estimates had important differences with the observed averages (Fig. 2c). Mean BE of the whole region was 7.7 Mg SOC ha^{-1}. Flooding Pampa had the highest mean BE (14 Mg SOC ha^{-1}) and also the lowest sampling density associated to its highest cover of grasslands and cultivated pastures (Fig. 3). Besides, this sub region has a high variability of soils types with extremely different characteristics and we grouped them into only one category (Table 2). Probably this classification masked differences among soils respect to SOC dynamics associated to land use change. We also evaluated T2 performance at the county scale excluding the data from the Flooding Pampa, and the determination coefficient increased from 0.46 to 0.73 (results not shown). It is likely that the low determination coefficient obtained with T2 method ($R^2 = 0.46$) at county scale may have been due, at least in part, to the uncertainty about the values observed from counties with low sampling densities.

At field scale, T2 method tended to sub estimate SOC stocks of CL, but the determination coefficient was higher than the obtained at county scale ($R^2 = 0.60$). The regression line had a $\beta_0 = 6.42$ Mg SOC ha^{-1} and a $\beta_1 = 1$ (Fig. 6) and, therefore, T2 method sub estimated SOC stock in 6.42 Mg SOC ha^{-1}. Despite this, the

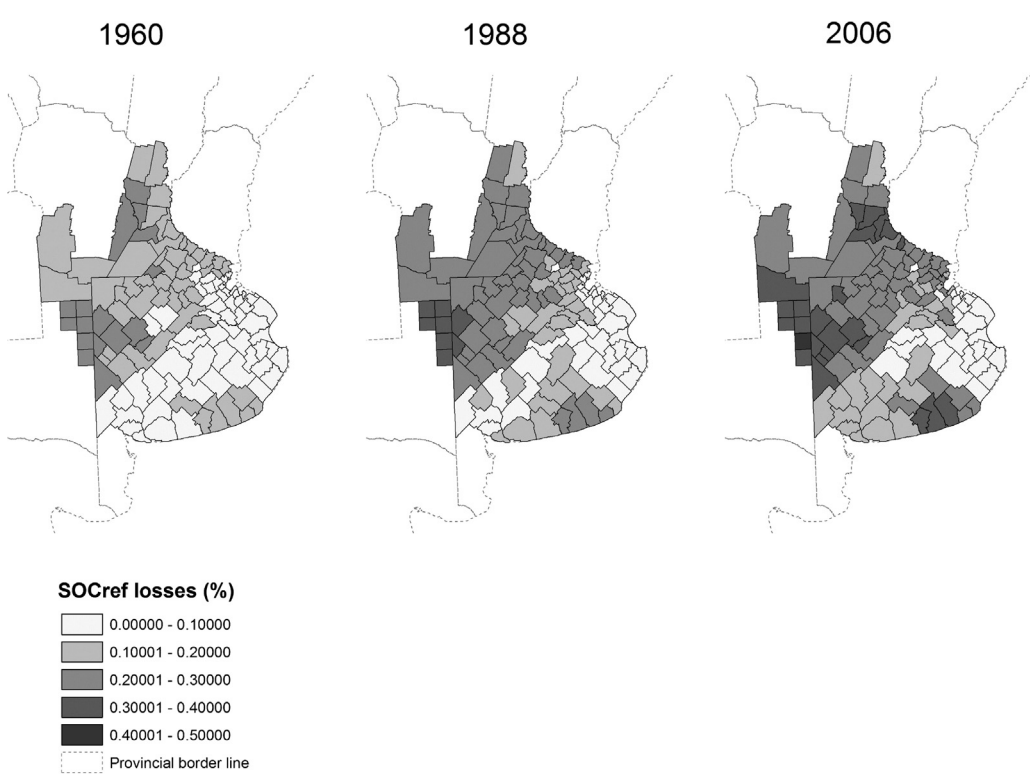

Fig. 6. Maps of reference soil organic carbon (SOCref) lost at county scale estimated with Tier 2 for 1960, 1988 and 2006.

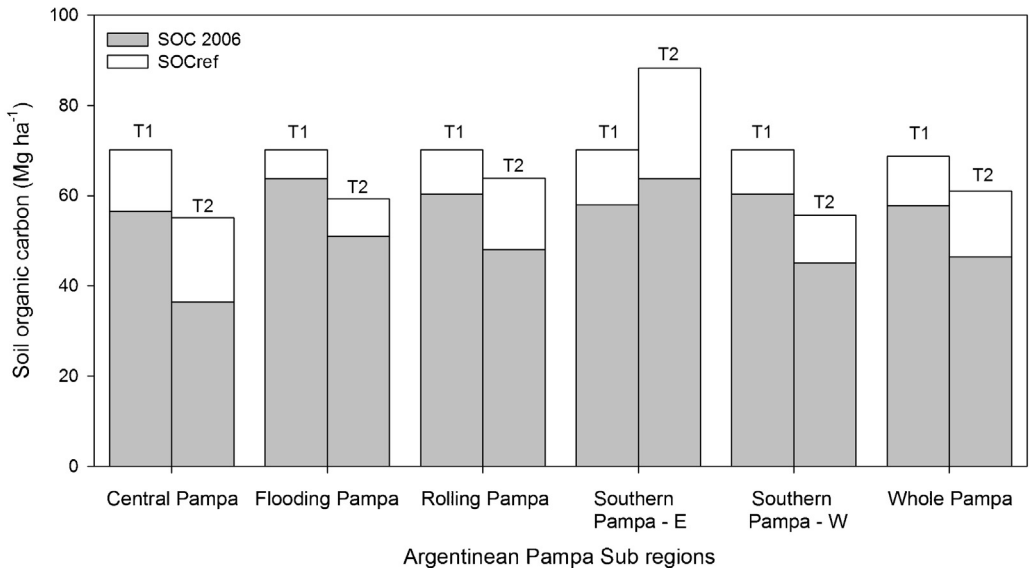

Fig. 7. Reference soil organic carbon (SOCref) and soil organic carbon estimated for 2006 (SOC 2006) by Tier 1 (T1) and Tier 2 (T2).

purpose of T2 method is not to do estimations at this scale but we run this model at field scale in order to assess its performance using the most accurate model inputs and reliable observed values as possible.

3.3. Land use change impact on soil organic carbon (SOC)

Since T2 method performance was better than T1's, T2 method was used to estimate the impact of land use change on SOC. Soil organic C losses expressed as a percentage of SOCref varied highly in space, ranging at 2006 from 2% to 48% among counties (Fig. 6). Sub regions with the highest estimated SOC losses were Central Pampa, Southern Pampa – E and Rolling Pampa, with 35%, 28% and 26% average SOC losses, respectively (Fig. 7). In CL, SOC losses estimated for Central Pampa, Southern Pampa – E and Rolling Pampa were 40%, 37% and 37%, respectively (results not shown). Alvarez (2001) used the Century model (Parton et al., 1987) and data of SOC stock from soil surveys, to estimate the effect of land use in the APR. The author concluded that in the Rolling Pampa about half of SOC had been lost, but SOC losses in other sub regions of the APR had been small. Our estimates were similar for the Rolling Pampa, but were different for the other sub regions, because we also estimated high SOC losses in Central Pampa and Southern Pampa. Sainz Rozas et al. (2011) reported SOC losses for CL in Rolling Pampa and Southern Pampa – E (42% and 37%, respectively, Sainz Rozas personal communication), and Michelena et al. (1988) had reported SOC losses between 21% and 56% for CL in the Rolling Pampa. Hence, our estimates are similar to those reported by these authors.

Between 1988 and 2006 crop yields increased and no-till management has increasingly been adopted by many farmers (AAPRESID, 2012). Despite these management changes were expected to lead to a positive effect on SOC content (Smith, 2004; Lal, 2011), SOC losses increased during this period. The rate of SOC loss for the whole region was 0.17 Mg SOC ha^{-1} yr^{-1} until 1988 and this rate increased to 0.19 Mg SOC ha^{-1} yr^{-1} between 1988 and 2006. This increase of SOC loss has been probably due to the increase of the replacement rate of GL by CL (INDEC, 2004; SIIA, 2013).

While our T2 method showed a better performance than T1 method, future research in the APR should aim to develop a T3 method in order to increase the reliability of estimates. The research of Caride et al. (2012) and Cerri et al. (2007) could be starting points to do this. Both studies use SOC simulation models to generate regional estimates of SOC changes. Also, an important tool developed to conduct regional-scale SOC inventories that should be taken account for T3 derivation purposes is the GEFSOC model (Easter et al., 2007).

4. Conclusion

Given that several conceptual limitations of T1 method were overcome with the T2 method, the latter was more realistic to conducting a regional inventory of SOC. This was supported by the important improvement of the estimates accuracy when using T2 method instead of T1 method. Besides, we advanced in a more objective and clear approach. This was due to the use of mathematical models that incorporate specific data to define change factors, instead of using descriptive categories which sometimes are not entirely clear.

On the other hand, Fc and Fg models were derived using a simple SOC simulation model (RothC) and local information about soils, climate, crop yields and rotation composition. This approach does not need empirical data from agricultural field trials to develop the T2 method. Thus, countries or regions without enough empirical data, could derive a similar T2 method using our proposed procedure. From our experience in the APR we summarize four key points to be considered to derive T2 method going through the approach proposed in this paper in other regions of the world:

- *Spatial stratification*. The stratification of the region under study should be done in order to obtain the most homogeneous as possible target sub units. We did not obtain a good fit in the Flooding Pampa and was probably due to the high heterogeneity of soils in this sub region. On the other hand, splitting Southern Pampa in two sub regions (Eastern and Western) resulted in a good decision, because the differences in SOC stock could be taken into account with T2 method.
- *RothC simulations*. It is necessary to identify which land uses and management practices are the most significant in the target region. The variables selected to fit the models to estimate change factors must be easily available information, in order to be able to easily apply the model obtained. In the APR we identified crop yields and rotations as the most important management practices which affect SOC in CL and this could be simulated with

RothC. However, despite tillage system is another key management practice to define SOC change in CL, its effect could not be simulated with RothC. This model was not developed for not tilled soils and therefore, we had to develop Fmg_2 based on some literature information. It should be explored the possibility of using some other simple SOC-change simulation model to generate information to estimate change factors associated not only to land use but also to different tillage systems.

- *Land use categories*. Land-use conversions in the APR occur mainly between two major land-use categories: CL and GL. This simplifies the study, because it is possible to assume that CL increase always comes from GL converted to CL. In other regions where most of the land-use conversion occurs between many land-uses categories (e.g. CL, GL, Forest Land and Wetlands) it will be difficult to apply this methodology without knowing which land-use category is converted to another land-use category.
- *Quality of data for validation and model inputs*. The lack of agreement between the T2 method estimates and observed values has been heavily influenced by the uncertainty associated with the counties with low sampling densities. Besides, our results shown that T2 method was improved when it was applied with accurate data (at field scale). Thus, it is very important to take into account the reliability of the input and validation information.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.agee.2013.12.021.

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