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Greenhouse gas inventories: Deriving soil organic carbon change factors and assessing soil depth relevance in Argentinean Semiarid Chaco

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ABSTRACT

Soil organic carbon (SOC) is the main terrestrial carbon (C) reservoir. Land use change has depleted SOC stocks and released large amounts of C dioxide (CO_2). Thus, the development of reliable tools for SOC stock monitoring at large scale is fundamental to face climate change. Argentinean Semiarid Chaco (ASC) is a deforestation hotspot, but CO_2 emissions from soil has been barely assessed. Deforested area was converted into cropland or grassland. We used empirical data to model SOC stocks under native forest (SOCref) and the RothC model to estimate SOC stock change factors under cropland (Fc) and grasslands (Fg) in the ASC. These SOCref's and stock change factors were applied in a Tier 2 (T2) C inventory, following the Intergovernmental Panel on Climate Change (IPCC) proposal. We used SOC vertical distribution models to estimate SOC stock at 0–100 cm soil depth from estimated SOC stocks at 0–30 cm, the default soil depth of IPCC C inventory method. The T2 was run for 1976 through 2012 and under three hypothetical land use change scenarios for 2012 through 2032. The scenarios were: i) land use change ceases, ii) land use change rate is the half of 1996–2012 land use change rate, and iii) land use change rate remains as in 1996–2012. Estimated average SOCref stock at 0–30 cm soil depth was 40 Mg C ha^{-1} and varied between 35 and 51 Mg C ha^{-1}. Cropland was the main fate of deforested area and the land use with lower SOC stocks. Stock change factors and SOC stocks estimated with T2 were within the range of the empirical data reported in the ASC. However, research about SOC dynamics and land use change is incipient in the ASC and more empirical information is needed to validate T2 estimations. Deforestation in the ASC leads to high CO_2 emissions from soil and the only scenario in which those emissions would be reduced is with deforestation cessation. Soil depth considered in greenhouse gas inventories is 0–30 cm, and this strongly underestimates CO_2 emissions. We demonstrated that this limitation could be overcome by using SOC vertical distribution models to estimate deep SOC stock (up to 1 m) from estimated surface SOC stock. Hence, these models could be used to improve CO_2 estimations from SOC inventories.

1. Introduction

The warming of the climate system is unequivocal. Earth's 2016 surface temperatures were the warmest since 1880, and 2016 was the third consecutive year to set a new record for global average surface temperatures (NASA, 2017). Climate change is among the main environmental crisis that faces humankind, and human activities are promoting it by increasing greenhouse gas (GHG) emissions (IPCC, 2013). The most important anthropogenic GHG is carbon (C) dioxide (CO_2), and its main sources due to human activity are primarily fossil fuel emissions and secondarily, net land use change emissions (IPCC, 2013). Soil organic C (SOC) stock is the main terrestrial C reservoir (Janzen, 2004) and land use change affects environmental processes that generate CO_2 fluxes from soil to atmosphere (emission) or from atmosphere to soil (sequestration) (Stockmann et al., 2013). Besides, SOC correlates positively with most of soil functions that support relevant ecosystem services to societies (Palm et al., 2007; Powlson et al., 2011; Banwart et al., 2015). Thus, in the context of international policy agendas on GHG emission mitigation, the development of reliable tools for SOC stock monitoring at large scale is fundamental (Lal, 2011; Stockmann et al., 2013).

The Intergovernmental Panel on Climate Change (IPCC) developed the *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, in which it is described a C inventory method (IPCC-CIM) to estimate anthropogenic GHG emission, including CO_2 emission from SOC changes (IPCC, 2006). The IPCC-CIM is based on three tiers. The higher

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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 (T3) development require the availability of much more information resources. Therefore, they would be feasible only in special and limited cases. At present, most of the developed countries that are listed in the Annex 1 of the United Nations Framework Convention on Climate Change (UNFCCC, 1992) have used T1 to report their agricultural soil GHG emissions (Lokupitiya and Paustian, 2006) and its uncertain accuracy could have led to severe misestimations.

In response to T1 limitation, Villarino et al. (2014) proposed the development of a T2 based on a slight modification of Eq. (1) and SOC stock change factor derivation using a data base obtained by simulations performed with the RothC model (Coleman and Jenkinson, 1996). Briefly, this approach has four steps: i) defining main land uses of the target region, ii) RothC model running to simulate SOC changes under a wide spectrum of land use, management practices and crop yield combinations, iii) calculating SOC stock change factors (i.e. SOC change ratios) from the results of RothC simulations, and iv) fitting linear models to predict the simulated stock change factors from simple variables obtainable at the regional scale. Using this approach, a significant improvement was obtained over T1 for the Argentinean Pampa Region with very little demand of 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. However, until now this approach to develop a T2 has only been done and validated in the Argentinean Humid-Subhumid Pampa Region (Villarino et al., 2014).

Agriculture expansion has led to the clearance or radical transformation of 70% of grasslands, 50% of savannas, 45% of temperate deciduous forests, and 25% of tropical forests in the whole world (Foley, 2011). Land use change, and particularly deforestation, produced strong environmental impacts, such as biodiversity loss, climate change, and soil degradation (Lal, 2001; Foley et al., 2007; Don et al., 2011; Smith et al., 2016). In South American Semiarid Chaco the highest rate of subtropical forest loss in the 21st century has occurred (Hansen et al., 2013), and approximately 62% of this region is within Argentina (Argentinean Semiarid Chaco, ASC) (Vallejos et al., 2014). The ASC region is a vast plain of about 29 Mha located at north-central Argentina (Fig. 1). Soils in this region are dominated by Mollisols (mainly Haplustolls and Argiustolls) and Alfisols (mainly Natracualfs and Haplustalfs), with loam and loam-silty textures (INTA, 1990). Native vegetation of this region is mainly a xerophytic forest (Morello et al., 2005). Deforestation rates in the ASC have increased exponentially since 1976, reaching a maximum value (2.5% yr^{-1}) between 2006 and 2012 (Vallejos et al., 2014). For the same period, Latin American and world deforestation rates were 0.51% yr^{-1} and 0.20% yr^{-1}, respectively (Seghezzo et al., 2011). Main drive forces of this land use change in the ASC were the high international prices of soybean (*Glycine* max (L.) Merr), the simplification and cost reduction of soybean cropping due to genetically-modified varieties (expanded over the whole Argentina) and no-till adoption (Gasparri and Grau, 2009; Gasparri et al., 2013), and the mean annual rainfall increase in the region (Barros, 2006).

Native forest clearance in the ASC modified C cycle by reducing and switching the aboveground net primary production to a more season-concentrated pattern. This ecosystem function change is associated with a decrease in ecosystem services provision (Volante et al., 2012) but also with an increase in CO_2 emissions (Gasparri et al., 2008). The impact of land use change on CO_2 emissions was estimated at regional scale in the South American Semiarid Chaco (Gasparri et al., 2008; De Sy et al., 2015; Baumann et al., 2016). However, SOC pool was scarcely assessed and remains as a black box in this region.

Most of SOC dynamics research had primarily been focused on the surface soil layers, around the top 30 cm of soil (IPCC, 2006; Don et al., 2011). This may be due to surface SOC stocks are key to define soil productivity and because deep soil sampling demands much more effort and resources. However, it has been reported that many land use changes clearly affect deep SOC stocks (Lorenz and Lal, 2005; Knops and Bradley, 2009; Poeplau et al., 2011; Villarino et al., 2017). Soil organic C balances in ecosystems should take into account the 40–100 cm soil depth, because this soil layer holds, on the average, 35% of total SOC in the first meter of soil (Jobbágy and Jackson, 2000). On the other hand, SOC turnover and microbial activity diminishes with soil depth (Fontaine et al., 2007). Thus, SOC stock in deep layers change slowly (Arai et al., 2007) which, in other words, means that C remains sequestered for longer periods.

The inherent variability of SOC stocks in the landscape (which is higher in natural ecosystems) hampers the detection of changes. Thus, high soil samples number are required for SOC changes detection within short periods (~ 10 yr) (Schrumpf et al., 2011). In order to improve the soil carbon auditing at farm scale, more cost-effective methods for direct SOC measurements were developed (De Gruijter et al., 2016). These findings are promising because they help to reduce cost and increase precision of SOC stocks estimations, among other advantages associated to field measurements (e.g. the site-specific knowledge feedback to farmers, (De Gruijter et al., 2016)). However, in developing countries such as Argentina, direct measurement methods for regional scale are economically unfeasible. Therefore, a more precise model approach to estimate SOC changes is needed. Simulation/prediction methods would help policy makers and enforcement agencies to control, recommend and/or enforce management practices to reduce SOC loss and soil degradation. Therefore, the main goals of this work were to i) test the suitability of the IPCC T2 based on RothC simulations to estimate SOC stock change factors (Villarino et al., 2014) to estimate CO_2 emission from soil linked to land use change in the ASC and ii) assess the relevance of soil depth in CO_2 emissions estimations.

2. Materials and methods

2.1. Land use change

Deforestation became a relevant factor of landscape transformation in the ASC between 1940 and 1950 (Morello et al., 2005). Therefore, we assumed that significant land use change within the study region started in 1945. Evaluation years for the IPCC-CIM were 1976, 1996 and 2012. These years were chosen because 1976–1996 and 1996–2012 represent two contrasting periods of the ASC's land use history.

The area of each unit of study of the ASC in each year was divided and classified into three land use categories: forest, cropland and grassland. The decrease in forest area (hereafter deforested area) was obtained from remote sensing estimations (Vallejos et al., 2014). Cropland area was taken from the Argentinean Integrated Agricultural Information System (SIIA, 2015).

To estimate the conversions among land use categories, the following assumptions were done: i) deforested area was due to conversion of forest into cropland or grassland (Baumann et al., 2016), ii) if in a given period cropland area increase was lower than deforested area, the difference was assigned to the conversion of forest into grassland, iii) if in a given period cropland area increase was higher than deforested area, the deforested area was assumed as conversion of forest into cropland and the difference as conversion of grassland into cropland, iv) if in a given period cropland area decreased, it was assumed it was due to the conversion of cropland into grassland, because we assumed that neither cropland nor grassland were converted back into forest (Baumann et al., 2016), and v) the area that is not either cropland nor grassland, is forest. With these assumptions, the study area was constant among evaluation years (Fig. 2), that is an explicit requirement of the IPCC-CIM (IPCC, 2006). Data describing cropland use (crops, yields,

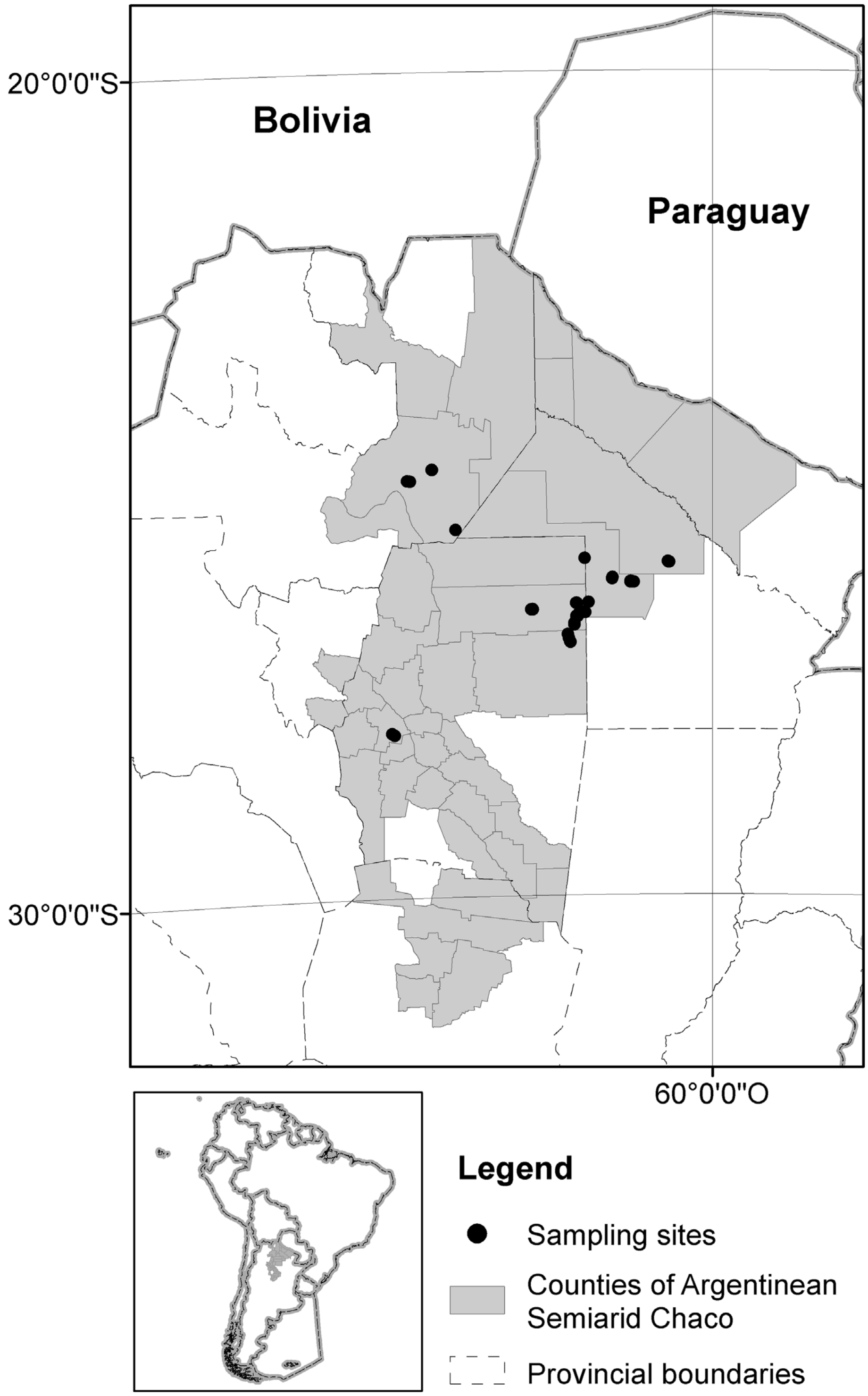

Fig. 1. Counties of Argentinean Semiarid Chaco. Black points indicate the location of 21 sampling sites used for model fitting. Eighteen out of those 21 sites were taken from Villarino et al. (2017) and the three others were located in Natural Reserves: Parque Nacional Copo (sampling coordinates: 25° 55′ 17″ S, 61° 43′ 7″ W), Parque Provincial Pampa del Indio (sampling coordinates: 26° 16′ 8″ S, 59° 58′ 16″ W), and Campo Experimental La María (sampling coordinates: 28° 1′ 16″ S, 64° 20′ 19″ W).

and tillage systems) was taken from the Argentinean Integrated Agricultural Information System (SIIA, 2015) and the Argentinean National Agricultural Census (INDEC, 2004). Given the county is the minimum spatial unit at which this information is available in Argentina, we selected this scale level for T2 estimations. Forty ASC counties were selected by overlapping the region and the politic division maps, and considering that a county integrated the ASC when 50% or more of its area fitted within the ASC.

2.2. Carbon inventory method Tier 1

Tier 1 and T2 are based on two simple equations to estimate SOC stocks (Eq. (1)) and C fluxes (Eq. (2)) (IPCC, 2006):

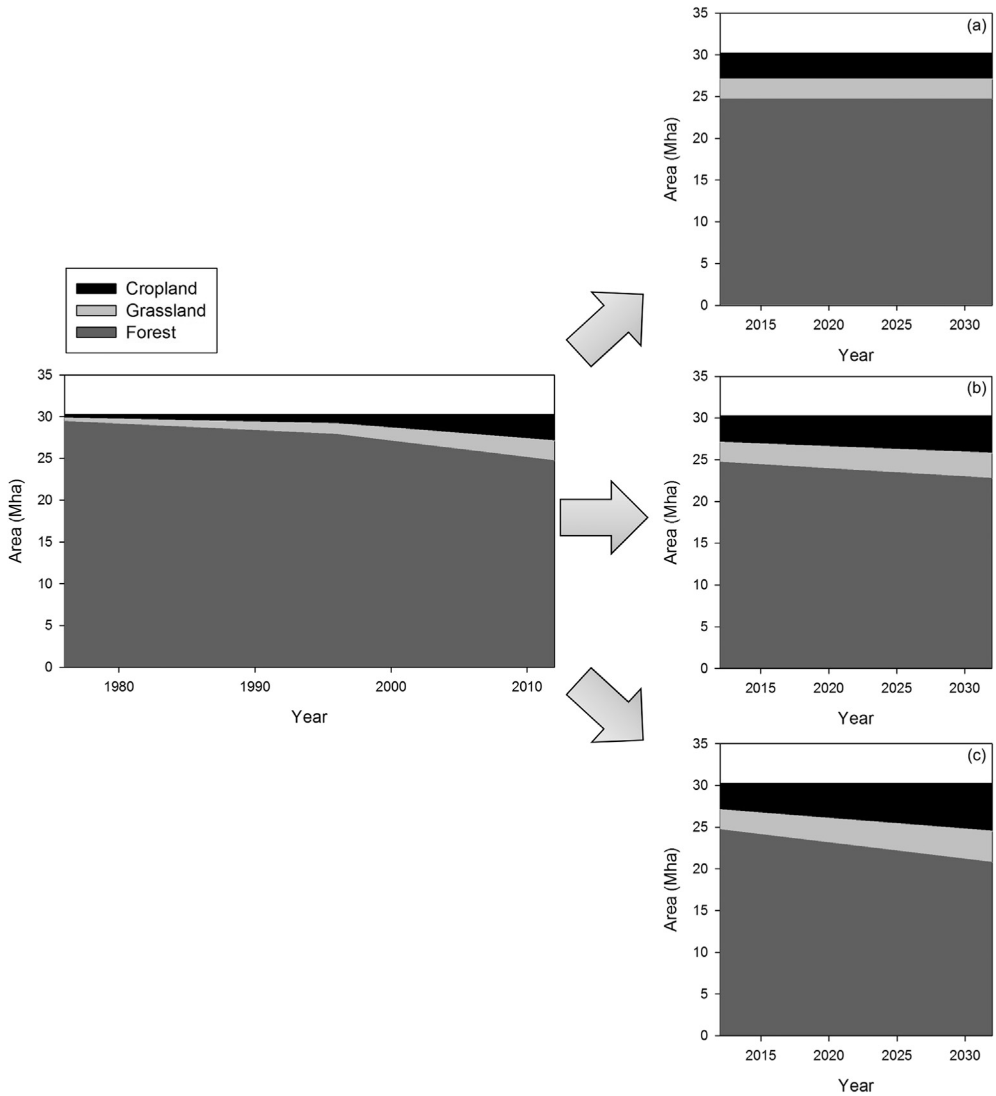

Fig. 2. Estimated land use area in 1976–2012 and in the three land use change scenarios for 2012–2032 (scenario without land use change (a), scenario with half of 1996–2012 land use change rate (b), and scenario with the same land use change rate as between 1996 and 2012 (c)).

$$SOC_{c,s,i} = SOCref_{c,s,i} \times Flu_{c,s,i} \times Fmg_{c,s,i} \times Fi_{c,s,i} \times A_{c,s,i} \quad (1)$$

$$\Delta C = (SOC_2 - SOC_1)/D \quad (2)$$

where $SOC_{c,s,i}$ is the estimated SOC stock (Mg C ha^{-1}) for the c-th climate zone, the s-th soil type, and the i-th management systems; SOCref is SOC stock under native vegetation (Mg C ha^{-1}); Flu is SOC stock change factor due to land use (dimensionless); Fmg is SOC stock change factor due to management regime (dimensionless); Fi is SOC stock change factor due to C input level to soil (dimensionless); A is land area (ha); ΔC is the annual change in SOC stock (Mg C ha^{-1} yr^{-1}); SOC_1 is SOC stock at the beginning of the inventory time period (Mg C ha^{-1}); SOC_2 is SOC stock in the last year of an inventory time period (Mg C ha^{-1}) (SOC_1 and SOC_2 are calculated using Eq. (1)); and D is time dependence of stock change factors (yr) (20 yr for T1 SOC stock change factors) (IPCC, 2006). According to the IPCC (2006), the information necessary to run T1 is based on climate, soil type and land use change of the target region. With this information, SOCref and stock change factors (Eq. (1)) could be obtained from default tables. For T2, SOCref and stock change factors (Eq. (1)) are not obtained from the global values estimated by the IPCC (IPCC, 2006) and have to be based on country- or region-specific data. On the other hand, to perform T3, more complex models and inventory measurement systems driven by high-resolution activity data that better capture variability for local conditions, should be taken into account (IPCC, 2006).

According to the T1 approach, SOC stock change in each county was estimated using Eq. (1) and Eq. (2). Counties were classified according to climate and soil types following IPCC (2006) guidelines using climate (Bianchi and Cravero, 2010) and soil (INTA, 1990) maps. All counties fell within "Tropical Dry" climate classification and 95% of the counties were classified as "high activity clay" soil and 5% of the counties as "low activity clay" soil (IPCC, 2006). Therefore, estimated SOCref with T1 was 38 Mg ha^{-1} for the counties classified as "high activity clay" and 35 Mg ha^{-1} for the counties classified as "low activity clay" (IPCC, 2006). Land use factor (Flu, Eq. (1)) was 0.58 for croplands and 1 for grassland (Table 1). Management factors (Fmg, Eq. (1)) associated to croplands were 1 for "Full tillage" and 1.17 for "No-till" (Table 1). Both management factor values were aggregated into only one Fmg for each county, through averaging both Fmg weighed by the area of the county corresponding to each tillage system. In 1976, the assigned input factor (Fi, Eq. (1)) for cropland corresponded to "low" category given that crops had low yields (Table 2). Starting from 1996, the assigned Fi for cropland corresponded to "medium" category due to crop yields increase (Table 2). For grassland, the assigned Fmg corresponded to "moderately degraded" category and the Fi corresponded to "medium" category. Grasslands had been degraded due to overgrazing (Abril and Bucher, 2001; Morello et al., 2005), but the degradation degree is hard

Table 1
Land use factor (Flu), management factor (Fmg) and carbon (C) input factor (Fi) of Tier 1 (T1) for Argentinean Semiarid Chaco ("tropical dry" climate category and "high clay activity" mineral soil category, IPCC, 2006).

Land use	Flu	Flu Error[a]	Management category	Fmg	Fmg Error[a]	C Input level	Fi	Fi Error[a]	Final factor[b]
Cropland	0.58	± 61%	Full-tillage	1.00	NA	Low	0.95	± 13%	0.55
			Full-tillage			Medium	1.00	NA	0.58
			Full-tillage			High	1.04	± 13%	0.60
			No-till	1.17	± 8%	Low	0.95	± 13%	0.64
			No-till			Medium	1.00	NA	0.68
			No-till			High	1.04	± 13%	0.71
Grassland	1.00	NA	Non-degraded	1.00	NA	Medium	1.00	NA	1.00
			Non-degraded			High	1.11	± 7%	1.11
			Moderately degraded	0.97	± 11%	Medium	1.00	NA	0.97
			Moderately degraded			High	1.11	± 7%	1.08
			Severely degraded	0.70	± 40%	Medium	1.00	NA	0.70
			Severely degraded			High	1.11	± 7%	0.78
			Improved	1.17	± 9%	Medium	1.00	NA	1.17
			Improved			High	1.11	± 7%	1.30

[a] + two standard deviations, expressed as a percent of the mean. NA denotes 'Not Applicable' (IPCC, 2006).
[b] Final stock factor was calculated as the product between Flu, Fmg and Fi, and represents the quotient between soil organic C (SOC) stock in the new land use at equilibrium and SOC stock under native condition. The default time period for stock changes factors is 20 yr and influence SOC stocks to a depth of 30 cm (IPCC, 2006).

to estimate. Therefore, we assumed the moderately degraded as the average condition.

2.3. Carbon inventory method Tier 2

The T2 method was applied as proposed in Villarino et al. (2014). Therefore, SOC stock in each county was estimated as the average SOC stock of each land use category (forest, grassland, and cropland) weighted by the area (Eq. (3)):

$$SOC_{it} = \sum_{j=1}^{3} SOC_{ijt} \times A_{ijt}/A_i \tag{3}$$

where SOC_{it} is the estimated SOC stock (Mg C ha^{-1}) of the i-th county at time t (yr); SOC_{ijt} is SOC stock (Mg C ha^{-1}) of the i-th county, under the j-th land use (j = 1,2,3, where 1 is for forest, 2 is for grassland and 3 is for cropland) at time t (yr); A_{ijt} is the area of the i-th county (ha), under the j-th land use at time t (yr); and A_i is the area (ha) of the i-th county within the ASC. The SOCijt was estimated through Eq. (4) and Eq. (5):

$$SOC_{iCt} = SOC_{iG(t-1)} \times Fc \times A_{iGC}/A_{iC} + SOC_{iF(t-1)} \times Fc \times A_{iFC}/A_{iC} + SOC_{iC(t-1)} \times Fc \times A_{iCC}/A_{iC} \tag{4}$$

$$SOC_{iGt} = SOC_{C(t-1)} \times Fg \times A_{iCG}/A_{iG} + SOC_{F(t-1)} \times Fg \times A_{iFG}/A_{iG} + SOC_{G(t-1)} \times Fg \times A_{iGG}/A_{iG} \tag{5}$$

where SOC_{iCt} is SOC stock (Mg C ha^{-1}) of the i-th county under cropland land use at time t (yr); SOC_{iGt} is SOC stock (Mg C ha^{-1}) of the i-th county under grassland land use at time t (yr); $SOC_{iG(t\text{-}1)}$ is SOC stock (Mg C ha^{-1}) of the i-th county under grassland land use at time t-1 (yr) (i.e. at the previous inventory year); $SOC_{iF(t\text{-}1)}$ is SOC stock (Mg C ha^{-1}) of the i-th county under forest land use at time t-1 (yr); $SOC_{iC(t\text{-}1)}$ is SOC stock (Mg C ha^{-1}) of the i-th county under cropland land use at time t-1 (yr); Fc is the stock change factor for cropland (dimensionless); Fg is the stock change factor for grassland (Fig. 3) (dimensionless); A_{iGC} is the area of grassland to cropland land use change (ha) for the i-th county; A_{iFC} is the area of forest to cropland land use change (ha) for the i-th county; A_{iCC} is the area of cropland remaining cropland (ha) for the i-th county; A_{iCG} is the area of cropland to grassland land use change (ha) for the i-th county; A_{iFG} is the area of forest to grassland land use change (ha) for the i-th county; A_{iGG} is the area of grassland remaining grassland (ha) for the i-th county; A_{iC} is the area of the i-th county for cropland land use (ha); and A_{iG} is the area of the i-th county for grassland land use (ha). Soil organic C stock under forest was assumed constant along the estimation period. Carbon fluxes were estimated with Eq. (2) and C mass was multiplied by 44/12 to convert C into CO_2, based on the ratio of molecular weights (IPCC, 2006).

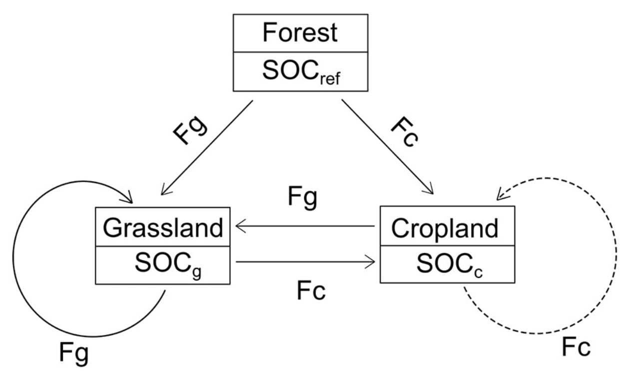

Fig. 3. Stock change factors for croplands (F_c) and for grasslands (F_g) used to estimate soil organic carbon under grassland (SOC_g) and cropland (SOC_c) in each land use change (Eq. (4) and Eq. (5)). Circular arrows indicate grassland remaining grassland (solid) and cropland remaining cropland categories (dashed). SOC_{ref}: soil organic carbon under forest. We assumed that neither cropland nor grassland were converted into forest for the studied periods.

Table 2
Average and standard deviations (between brackets) of crop yields and crop areas in each inventory year.

Inventory year	Cotton		Maize		Soybean		Sunflower		Wheat	
	Yield (Mg ha^{-1})	Area (%)	Yield (Mg ha^{-1})	Area (%)	Yield (Mg ha^{-1})	Area (%)	Yield (Mg ha^{-1})	Area (%)	Yield (Mg ha^{-1})	Area (%)
1976	0.8 (0.3)	19.3 (27.8)	1.1 (0.7)	51.9 (32.9)	0.7 (0.8)	12.2 (25.5)	0.3 (0.4)	2.8 (6.1)	0.8 (0.6)	13.9 (15.9)
1996	1.2 (0.5)	27.7 (36.4)	3.0 (0.7)	43.8 (35.2)	1.3 (1.0)	23.0 (25.1)	0.6 (0.7)	1.1 (3.3)	0.7 (0.8)	4.4 (8.8)
2012	1.6 (0.8)	13.7 (19.4)	3.5 (1.3)	26.7 (19.9)	1.4 (0.7)	47.4 (24.9)	0.6 (0.6)	1.7 (3.9)	1.0 (0.7)	10.4 (8.1)

Soil depth considered by the IPCC-CIM to estimate SOC stock change due land use change is 0–30 cm (IPCC, 2006). However, recent studies show that forest to cropland conversion could affect SOC stocks up to 1 m soil depth (Ciuffoli, 2013; Osinaga et al., 2016; Villarino et al., 2017). Therefore, we used SOC vertical distribution models (Eq. (6) and Eq. (7), Villarino et al., 2017) to estimate SOC stock under forest and cropland at 0–100 cm soil depth from estimated SOC stocks at 0–30 cm.

$$y_C = 1 - 0.975^x \tag{6}$$

$$y_F = 0.048\ x^{0.67} \tag{7}$$

where y_C is accumulated SOC proportion in soil under cropland, y_F is accumulated SOC proportion in soil under forest and x is the soil depth (cm). We could not find SOC vertical distribution models for ASC grasslands. Therefore, to estimate SOC stock at 0–100 cm soil depth from estimated SOC stocks at 0–30 cm of grasslands, we used the SOC vertical distribution for the "tropical grassland/savanna" land use category reported by Jobbágy and Jackson (2000).

To assess SOC changes in the near future, T2 was also run under three hypothetical land use change scenarios for the period 2012–2032. Land use change scenarios were: a) land use change ceases and the area of each land use category in 2032 is the same as in 2012, b) land use change rate in 2012–2032 is reduced to the half of 1996–2012 land use change rate for all categories (i.e. forest to cropland, forest to grassland, grassland to cropland and cropland to grassland), and c) land use change rate in 2012–2032 is the same as 1996–2012 land use change rate for all land use change categories (Fig. 2). In all hypothetical scenarios crop yields and crop proportions were assumed to remain as in 2012 (Table 2).

2.4. Soil organic C under native forest (SOCref)

Linear models to predict SOC under native forest (SOCref) as a function of soil sand content and mean annual precipitation were fitted, since it is well known that these predictor variables strongly determine SOC stocks (Post et al., 1982; Álvarez and Lavado, 1998; Jobbágy and Jackson, 2000). Linear models were fitted with the lm function from stats package, version 3.4.3 (R Core Team, 2017). The best model was selected through graphical analysis of the residuals and the highest determination coefficient (R^2) criterion. Soil organic C stock data for model fitting was obtained from soil samples from 21 sites under native forest. Eighteen out of those 21 sites were taken from Villarino et al. (2017) and the three other sites were sampled for this work (Fig. 1). In each site, composite soil samples (15–20 subsamples) at 0–30 cm soil depth were collected using a 2 cm diameter soil corer. The 0–30 cm soil depth was selected due to two reasons: 1) it is the recommended soil depth by the IPCC, and we wanted to compare T1 against T2, and 2) the RothC model was developed for topsoil and we wanted to use SOCref stocks to initialize cropland and grassland simulations (see Sections 2.5 and 2.6). Total wet weight of each sample was recorded. After homogenization, an aliquot was taken from each fresh soil sample and then oven dried at 105 °C to determine soil moisture content. Total dry weight was divided by the total volume (volume of each soil core ∗ number of subsamples in the composite sample) to estimate soil bulk density. The rest of the sample was oven dried at 30 °C, ground and then sieved through 2 mm mesh, identifiable plant material was eliminated manually. Soil organic C concentration was determined by wet combustion, maintaining reaction temperature at 120 °C for 90 min (Schlichting et al., 1995). Bulk density was used to convert SOC concentration into SOC stocks at 0–30 soil depth (Mg ha^{-1}).

Mean annual precipitation of each sampling site was determined using climate maps (Bianchi and Cravero, 2010). The best model was selected through graphical residual analyses to check model assumptions and with the highest R^2 criterion. The best model was utilized to estimate SOCref of each county. Mean annual precipitation and soil sand content of each county were obtained from climate (Bianchi and Cravero, 2010) and soil maps (INTA, 1990; Angueira et al., 2007).

2.5. Stock change factor for croplands (Fc)

Main crops in the ASC for 1976–2012 period, were cotton (*Gossypium hirsutum* L.), maize (*Zea mays* L.), soybean, sunflower (*Helianthus annuus* L.), and wheat (*Triticum aestivum* L.) (SIIA, 2015). A total of 11 historical and current crop rotations were defined for the ASC based on querying to local experts from the Argentinean National Institute of Agricultural Technology. These rotations were used to simulate SOC stock change with the RothC model (Coleman and Jenkinson, 1996) at 0–30 cm soil depth, under three soil clay percentage levels (3%, 13% y 20%), with three rotation yield levels, and under two tillage systems (full tillage and no-till). Therefore, each crop rotation was used to simulate SOC stock change under 18 combinations of those factors. The three soil clay levels taken into account correspond to the minimum, average and maximum values from a data base containing 83 soil profiles from the ASC (Angueira et al., 2007). The three crop yield levels corresponded to the average minus two standard deviations (low), the average (medium) and the average plus two standard deviations (high) of each crop for the 1976–2012 period (SIIA, 2015). Yield levels were randomly assigned to crops integrating the 11 rotations, and this procedure was repeated three times for each one of them. Random allocation of yield levels was done with the restriction that total amount of low, medium and high levels in all three repetitions per crop rotation, had to be the same.

Carbon inputs were estimated from crop yields. For these estimations it was assumed that: i) harvest indexes of cotton, maize, soybean, sunflower, and wheat were 0.32 (Peterlin and Mondino, 2004), 0.45, 0.40, 0.45 and 0.35 (Studdert and Echeverría, 2000), respectively, ii) root/aboveground biomass ratios of cotton, maize, soybean, sunflower, and wheat were 0.38, 0.38, 0.35, 0.38 y 0.45 (Buyanovsky and Wagner, 1986), respectively, iii) the proportion of roots in the top 30 cm of the soil is 0.95 for all crops (Buyanovsky and Wagner, 1986), and iv) C concentration in the biomass (above- and belowground) is 43% (Sánchez et al., 1996). 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. All scenarios were simulated during 10, 20, 30, 40, and 50 years. The starting points were forest at equilibrium, obtained by simulating C inputs during 10,000 years. The C inputs were estimated using the average SOCref (see Section 2.3.) and the inverse mode of RothC (Coleman and Jenkinson, 1996).

The Fc's were calculated as the ratio between the estimated SOC stock and the estimated SOC stock in a previous time of the same scenario. With all possible combinations, 2970 data of Fc were obtained. Then, multiple linear regression models were fitted to predict Fc using soil clay content (g 100 g^{-1}), 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 in the rotation, and tillage system as predicting variables. Many of these variables were selected because they could be obtained from the Argentinean Integrated Agricultural Information System (SIIA, 2015) and the Argentinean National Agricultural Census (INDEC, 2004). Along the analyzed periods (1945–1976, 1976–1996, 1996–2012), it was assumed that the area that changed from one land use to another occurred at a constant rate. Therefore, the average age of a new cropland area within a period was calculated as the difference between the ending and the starting years of the period divided by two (e.g. 1 Mha of forest in 1996 that changed to cropland in 2012 was 8 years old ((2012–1996)/2 = 8)). This land use time was used to estimate Fc for forest to cropland or grassland to cropland conversions (Fig. 3). To estimate Fc for cropland remaining cropland (Fig. 3) the time used was the difference between the ending and the starting years of the period. Finally, the best model was selected through graphical analyses of the residuals and the highest

R^2 criterion.

2.6. Stock change factor for grassland (Fg)

Cultivated grasslands in the ASC are mainly composed by megathermic grasses (Barbera et al., 2014). Dry matter (DM) productivity of these grasses is strongly determined by mean annual precipitation, and vary from 4.6 Mg DM ha^{-1} to 6.7 Mg DM ha^{-1} when mean annual precipitation varies from 600 mm to 800 mm (De León, 2004). Counties were grouped according to their mean annual precipitation in three intervals: i) 487–642 mm, ii) 643–797 mm, and iii) 798–875 mm. Grassland DM productions were assumed as 4.6, 5.7, and 6.7 Mg DM ha^{-1} for the i), ii) and iii) intervals, respectively (De León, 2004; Cornacchione and Reineri, 2008). These three DM production levels of grasslands were used to simulate SOC stock changes with RothC (Coleman and Jenkinson, 1996), under three soil clay content levels (see Section 2.4.), during 10, 20, 30, 40, and 50 years, and starting from five initial SOC stocks obtained from cropland simulations (55, 42, 36, 30, and 18 Mg C ha^{-1}). In order to estimate C inputs from grassland DM productions, the following assumptions were done: i) root/aboveground biomass ratio was 0.45 (Veneciano and Frigerio, 2003), ii) root proportion in the top 30 cm of soil (Jackson et al., 1996) was 0.83, and iii) C concentration in the whole biomass (above- and belowground) was 37% (Maryol and Lin, 2015).

The Fg's were calculated in the same way as for Fc (see Section 2.4.), obtaining 675 Fg associated to the different situations simulated. Then, multiple linear regression models were fitted to predict Fg using soil clay content (g 100 g^{-1}), initial SOC stock, elapsed time under grassland (yr), and DM production level as predicting variables. The average age of a new grassland area within a period was calculated as the difference between the ending and the starting years of the period divided by two (see Section 2.4.). This land use time was used to estimate Fg for forest to grassland or cropland to grassland conversions (Fig. 3). To estimate Fg for grassland remaining grassland (Fig. 3) the time used was the difference between the ending and the starting years of the period. Finally, the best model was selected through graphical analyses of the residuals and the highest R^2 criterion.

3. Results and discussion

3.1. Stock change factors

Selected models to predict Fc and Fg showed very good fit (R^2 = 0.89 and R^2 = 0.90, respectively, Table 3). Hence, SOC changes simulated with RothC could be predicted with linear models (Table 3).

Stock change factors for forest to cropland and forest to grassland conversions (Fc and Fg, respectively), were always < 1. This indicates that deforestation, whether into grassland or into cropland, always decreased SOC stocks (Fig. 4). 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. 4). The Fc for cropland remaining cropland was always lower than the Fg for grassland remaining grassland (Fig. 4). This means that cropland remaining cropland produced higher proportional losses of SOC stock than grassland remaining grassland.

The Fc for forest to cropland conversion grew from 1976 through 2012 (Fig. 4). This could be explained by the model parameters in the Fc model (Table 3). First, the value of the weighted yield parameter, was positive (Table 3), and the yield of all crops grew from 1976 through 2012 (Table 2). Second, the estimated parameter for no-till, was positive (Table 3), and no-till adoption by farmers grew exponentially from 1990s to present (AAPRESID, 2012). The sign of these parameters is in agreement with the empirical evidence reported in other works. Soil organic C stocks are positively correlated with C inputs and, therefore, also positively correlated with crop yields (Studdert and Echeverría, 2000; Ogle et al., 2005; Álvarez et al., 2011). On the other hand, switching from full tillage to no-till strongly affects SOC dynamics and, in many situations, causes SOC accumulation near soil surface (West and Post, 2002; Steinbach and Álvarez, 2006; Angers and Eriksen-Hamel, 2008). Third, looking at crop proportion (%) in the rotation, cotton had the most negative estimated parameter and wheat the most positive estimated parameter (Table 3). Between 1996 and 2012, the proportion of cotton in the rotation decreased 14% and wheat proportion increased 6% (Table 2). Summer crops (cotton, maize and soybean) are the main cultivated crops in the ASC. When winter-spring crops (wheat and sunflower) are cultivated, the soil remains covered for more time along the year because summer crops are cropped immediately after winter-spring crops in the same year. This soil cover increase has a positive effect on SOC stock (Poeplau and Don, 2015) and could explain why estimated parameters for wheat and sunflower are more positive than the estimated parameters for cotton, maize and soybean. Fourth, the estimated parameter for time was negative (Table 3). Cropping ages for forest to cropland conversions were assumed 16, 10 and 8 years old, for 1976, 1996 and 2012, respectively. Thus, the lower cropping age in the later periods also led to increased Fc value. It takes long time for SOC to respond to land use change (Dalal and Mayer, 1986; Dean et al., 2012) and this could explain why the estimated parameter for time was negative (Table 3). As time under cropland increases, SOC loss also increases. Villarino et al. (2017) evaluated 21 sites of forest to cropland conversion in the ASC and fitted a logarithmic model (R^2 = 0.77) to predict SOC changes as a function of cropping age. For 16, 10 and 8 yr under cropping after deforestation, that model (Villarino et al., 2017) predicted Fc's of 0.75, 0.85 and 0.90, respectively. The Fc's estimated with the model developed for this T2 (Table 3) for the same cropping ages were 0.77, 0.84 and 0.91 (Fig. 4). Therefore, the degree of agreement between studies, was high.

With T1, the estimated stock change factors for forest to cropland

Table 3
Summary of fitted linear models to predict stock change factor for croplands (Fc) and for grassland (Fg). Levels of statistical significance (P): *P < 0.05, **P < 0.01 and ***P < 0.001.

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

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^{-1}, DM-5.7 = 0 and DM-6.7 = 0, when DM production is 5.7 Mg DM ha^{-1}, DM-5.7 = 1 and DM-6.7 = 0, and when DM production is 6.7 Mg DM ha^{-1} DM-5.7 = 0 and DM-6.7 = 1. The asterisk (*) indicates interactions between predictor variables. The adjusted R^2 of Fc and Fg models were 0.89 and 0.90, respectively.

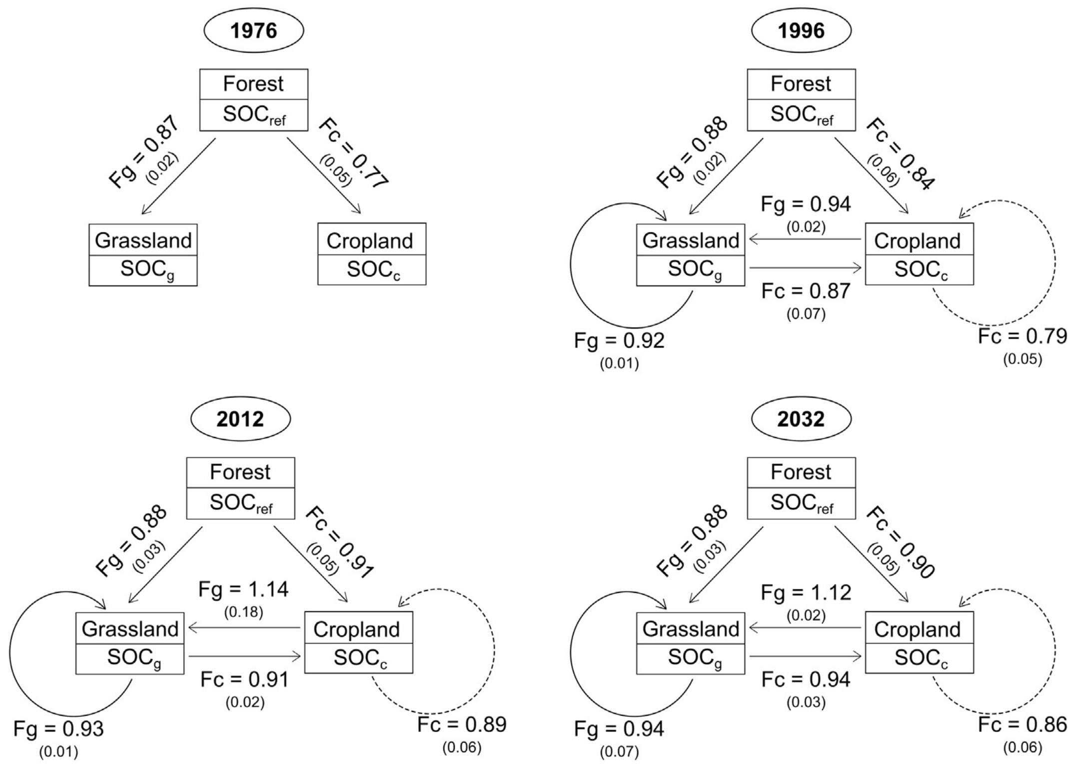

Fig. 4. Stock change factors for croplands (F_c) and for grasslands (F_g) used to estimate soil organic carbon changes in grassland (SOC_g) and cropland (SOC_c) for each evaluation year (bold number inside ovals). Circular arrows indicate grassland remaining grassland (solid) and cropland remaining cropland categories (dashed). SOC_{ref}: soil organic carbon under forest. Numbers between brackets are standard deviations.

conversion are 0.55 in 1976 (assuming full tillage and low carbon inputs, Table 1), 0.58 in 1996 (assuming full tillage and medium C inputs, Table 1) and 0.68 in 2012 (assuming no-till and medium C inputs, Table 1). All these T1 factors are below the estimated Fc's in this work and by Villarino et al. (2017). Thus, it is likely that estimated SOC stocks with T1 would have been strongly underestimated, and, consequently, CO_2 emissions in forest to cropland category, overestimated. On the other hand, the estimated SOC stocks with T1 for cropland remaining cropland category would have grown from 1976 to 1996 and from 1996 to 2012. This is because the C input factor (Fi) changed from 0.95 to 1.00 (Table 1) between 1976 and 1996, and the management factor (Fmg) changed from in 1.00 to 1.17 in no-till area (Table 1) between 1996 and 2012. However, with our T2, the Fc for cropland remaining cropland was always lower than 1 (Fig. 3), indicating that SOC stocks always decreased under cropland. With T1, the accumulated CO_2 emission from SOC changes in cropland (i.e. forest to cropland, grassland to cropland and cropland remaining cropland categories) between 1976 and 2012 was 143,058 Gg CO_2. However, with our T2 it was 67,156 Gg CO_2. The T1 estimation is 113% higher than T2 estimation. Thus, the net balance of T1 between the CO_2 emission overestimation in forest to cropland category and the CO_2 emission underestimation in cropland remaining cropland category, is a great CO_2 emission overestimation.

The Fg's for forest to grassland conversion estimated with our T2 were between 0.87 and 0.88. Caruso (2008) studied 11 sites in the ASC where forest changed to grassland, and the average SOC change under grassland was −24% (Fg = 0.76). However, this average resulted from an extremely high range, with a maximum of 6% (Fg = 1.06) and a minimum of −43% (Fg = 0.57). No relation between those changes and time since land use change were reported. Probably this relation was not detected because soil samples and/or time were not enough (Schrumpf et al., 2011). In other sites of the ASC, Ciuffoli (2013) observed −30 and − 10% SOC changes at 0–30 cm depth for 4 and 31 yr since forest to grassland conversion, respectively (Fg 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 with T2 (Table 3, Fig. 4) have a moderate degree of agreement with the mean of reported values (Caruso, 2008; Ciuffoli, 2013).

In this work, the estimated T1 stock change factor for forest to grassland conversion in the ASC was 0.97, because a "moderately degraded" condition was assumed (IPCC, 2006). However, the allocation of T1 stock change factor is quite subjective due to categories that describe grassland conditions are based on qualitative criteria. It is likely that many situations between severely degraded grassland with medium C inputs (Fg = 0.7, Table 1) and improved grassland with high C inputs (Fg = 1.3, Table 1) could be found in the ASC grasslands.

3.2. Spatial distribution of estimated SOCref and average SOC stocks

The selected model to estimate SOCref stocks (Eq. (8)) showed an R^2 = 0.68 and a P-value < 0.0001.

$$SOCref = 31.78 + 0.0007441 \times (P/S) \times P \tag{8}$$

where SOCref is SOC stock under forest (Mg C ha^{-1}), P is mean annual precipitation (mm), and S is soil sand content (g 100 g^{-1}). Average SOCref stock for the ASC was 40 Mg C ha^{-1} and varied between 35 and 51 Mg C ha^{-1} (Fig. 4). The highest SOCref stocks were estimated for the north-east and south-east of the ASC, whereas the lowest SOCref stocks were estimated for the center-east. Between 1976 and 2012, the average SOC stocks (Eq. (3)) were estimated as maintaining similar to SOCref at north and south of the ASC, whereas a tendency to SOC decrease was estimated in the central ASC (Fig. 5). In 2032, SOC decrease expanded towards south and north of the ASC, without important differences among hypothetical scenarios (Fig. 5).

The estimated SOCref stock with the T1 for the ASC was 38 Mg C ha^{-1} ("tropical dry" climate category and "high clay activity" mineral soil category, IPCC, 2006). However, with our T2 the estimated

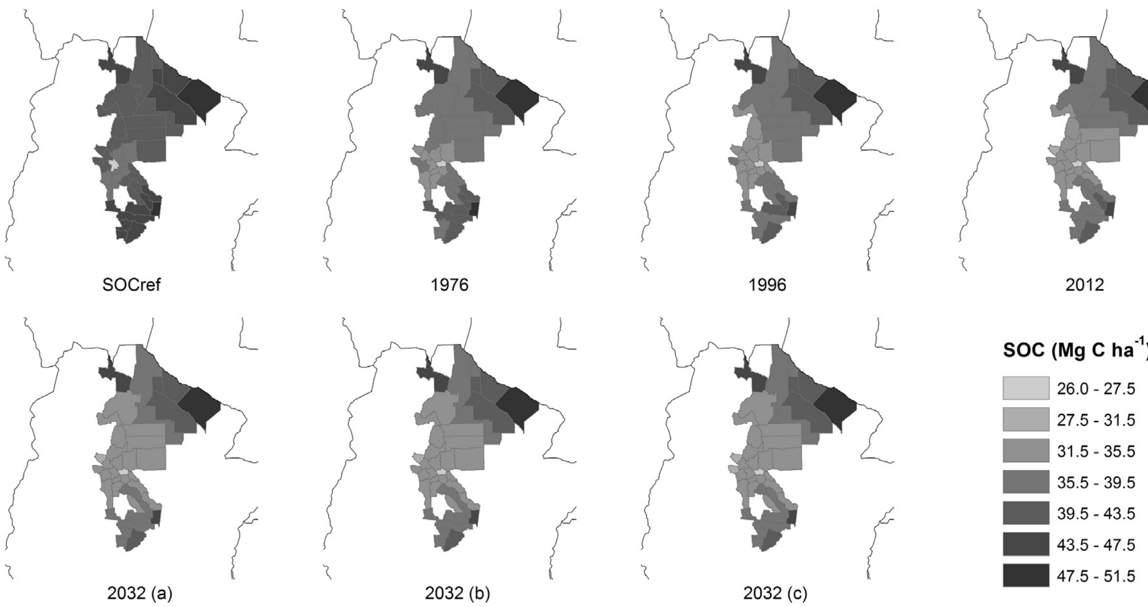

Fig. 5. Soil organic carbon under forest (SOCref) and average soil organic carbon (SOC) stocks at 0–30 cm depth in the Argentinean Semiarid Chaco counties in 1976, 1996, 2012, and 2032 for the three land use change scenarios for 2012–2032 (scenario without land use change (a), scenario with half of 1996–2012 land use change rate (b), and scenario with the same land use change rate as between 1996 and 2012 (c)).

average SOCref stock was 40 Mg C ha^{-1}, with a range between maximum and minimum of 16 Mg C ha^{-1}. Thus, there is a high degree of agreement between tiers regarding SOC stock average of the ASC, but the average estimated with our T2 showed high spatial variability that would not be taken into account with T1 (Fig. 5). In the north-west of the ASC, Abril and Bucher (2001) measured 71 and 31 Mg C ha^{-1} in *highly restored* and *moderately restored* forest conditions, respectively. The SOCref estimated with our T2 for this work is close to the *moderately restored* condition reported by Abril and Bucher (2001), which is more representative of forest condition at present (Morello et al., 2005), than to the *highly restored* condition.

3.3. Land use change, SOC loss and CO_2 emissions

The total area of the 40 analyzed counties comprised 30 Mha. Deforested area increased seven times from 1976 to 2012, reaching approximately 5.5 Mha in this last year (Fig. 2). Cropping was the main fate of this cleared area and occupied 10% of the ASC, whereas grassland occupied only 8% of the region (Fig. 2). Soil organic C stock ranking among land uses estimated with our T2 (forest > grassland > cropland, Fig. 6), agrees with the global tendency (Guo and Gifford, 2002; Don et al., 2011; Smith et al., 2016). Osinaga et al. (2016) and Ciuffoli (2013) measured SOC stocks at 0–100 and at 0–90 cm soil depth, respectively, in forest, grassland, and croplands. Osinaga et al. (2016) evaluated sites located in the central part of the ASC and Ciuffoli (2013) evaluated sites located in the north-western part. In the first study, the authors observed that average SOC stocks were: 119 Mg C ha^{-1} in forest, 88 Mg C ha^{-1} in grassland, and 75 Mg C ha^{-1} in cropland. In the second study, the authors reported average SOC stocks of 73 Mg C ha^{-1} in forest, 52 Mg C ha^{-1} in grassland, and 54 Mg C ha^{-1} in cropland. In 2012, our estimated SOC stocks at 0–100 cm soil depth, were 84 Mg C ha^{-1} in forest and 57 Mg C ha^{-1} in cropland (Fig. 6). Our estimated SOC stocks were between those reported by Osinaga et al. (2016) and Ciuffoli (2013), but they were closer to Ciuffoli (2013). On the other hand, the reported SOC stock differences between forest and cropland were 44 Mg C ha^{-1} (Osinaga et al., 2016) and 19 Mg C ha^{-1} (Ciuffoli, 2013), and our estimated difference was 27 Mg C ha^{-1}. Our estimation for the whole ASC fell in between the reported values, in specific places within the ASC. Therefore, we can consider that it is not far away from reality.

In semiarid environments, wind erosion is a major process that could alter soil properties and SOC stocks, both in natural and agroecosystems. Generally, wind erosion occurs in cultivated soil and the sediments are transported to naturals ecosystems (Iturri et al., 2016). Given the complexity of wind erosion process, we could not include these effects in our Tier 2. It is likely that SOC stock under forest has

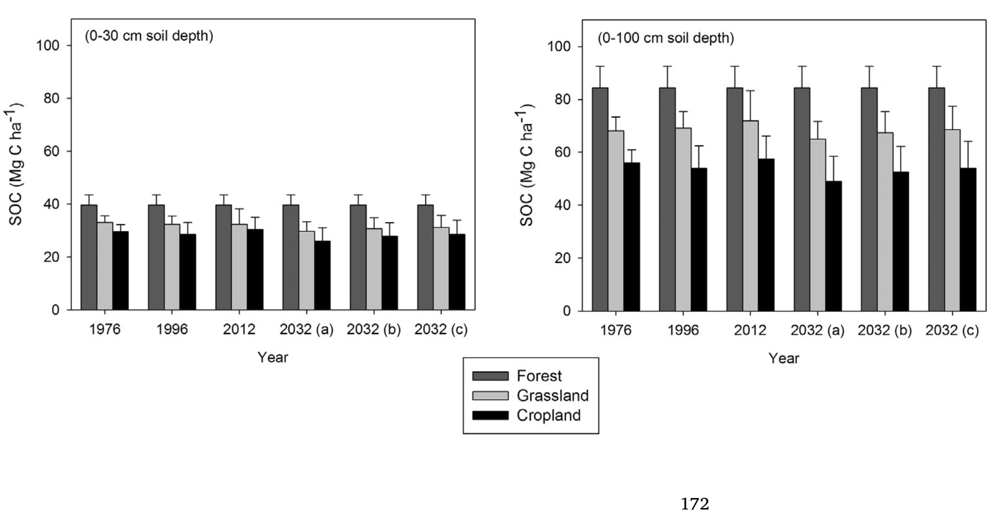

Fig. 6. Soil organic carbon (SOC) stocks at 0–30 cm (left panel) and at 0–100 cm (right panel) soil depths in 1976, 1996, 2012, and 2032 for the three land use change scenarios for 2012–2032 (scenario without new deforestation (a), scenario with half of 1996–2012 deforestation rate (b), and scenario with same deforestation rate as between 1996 and 2012 (c)).

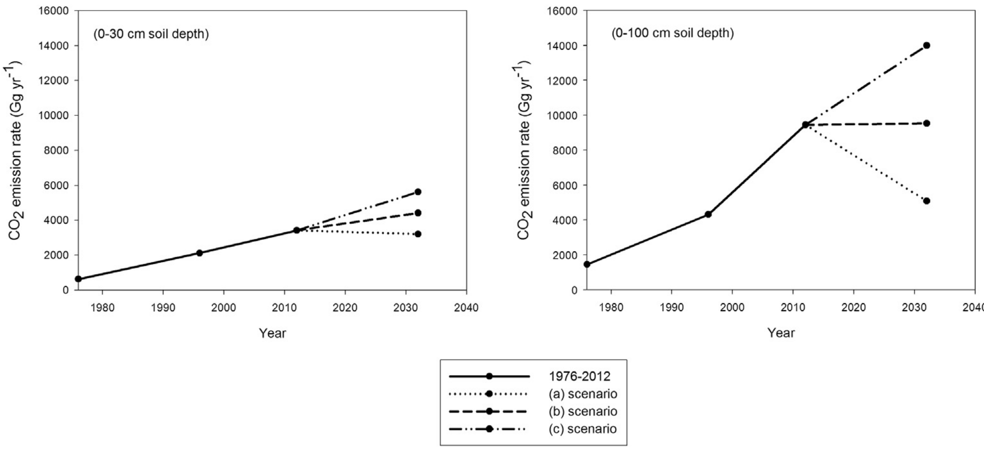

Fig. 7. Estimated carbon dioxide (CO_2) emission rates at 0–30 cm (left panel) and at 0–100 cm (right panel) soil depths in 1976–2012 and in the three land use change scenarios for 2012–2032: scenario without land use change (a), scenario with half of 1996–2012 land use change rate (b), and scenario with the same land use change rate as between 1996 and 2012 (c).

changed along the analyzed period, adding some uncertainty in our SOCref estimation and, consequently, in our CO_2 emission estimations too.

Soil organic C stocks under cropland decreased across time, with the exception of the period 1996–2012, for which a slight increase respect to 1976–1996 was estimated (Fig. 6). This period corresponds to the highest increase of forest to cropland conversion area (Fig. 2) and with the highest Fc for this land use change (0.91, Fig. 4). Therefore, the incorporation of new area with relative high SOC stocks to cropping led to an increase in the average SOC stock. This also explains why among hypothetical scenarios, the higher SOC stock under cropland was estimated under the scenario with higher deforestation rate (2032 (c), Fig. 6) and the lowest SOC stock under cropland was estimated under the scenario without deforestation (2032 (a), Fig. 6).

Carbon dioxide emission rates increased across time and were largely higher when soil depth taken into account changed from 0 to 30 to 0–100 cm (Fig. 7). This could be attributed to the fact that soil under forest has different SOC vertical distribution respect to croplands and keeps higher proportions of total SOC in deeper soil layers (40–100 cm) (Villarino et al., 2017). Between 1996 and 2012, the estimated CO_2 emission rate considering 0–100 cm soil depth was 176% higher than the estimated considering only 0–30 cm soil depth (Fig. 7). At 0–100 cm, CO_2 emission rate was highly sensitive to the hypothetical scenarios. The land use change cessation led to a fast reduction in the CO_2 emission rate (46% reduction respect to 2012, Fig. 7) while if 2012–2032 land use change rate remained as in 1996–2012, the T2 estimated a high CO_2 emission rate increase (48% increase respect to 2012, Fig. 7). These differences in the CO_2 emission rate among scenarios were lower at 0–30 cm soil depth (Fig. 7).

4. Conclusion

Stock change factors and SOC stocks estimated with our T2 were within the range of the empirical data reported in the ASC. In croplands, management effects on SOC changes were well represented through the Fc model, at least respect in SOC change direction, due the signs of model coefficients are in agreement to the present knowledge about SOC dynamics. However, research about SOC dynamics and land use change is incipient in the ASC and more empirical information is needed to validate our T2 estimations.

Deforestation in the ASC leads to high CO_2 emissions from soil and the only scenario where those emissions would be reduced is with deforestation cessation. Soil depth considered in GHG inventories is 0–30 cm, and this strongly underestimates CO_2 emissions. This limitation was overcome by using SOC vertical distribution models to estimate deep SOC stock (up to 1 m) from estimated surface SOC stock. Hence, these models could be used to improve CO_2 estimations from SOC inventories.

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