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Soil organic carbon changes simulated with the AMG model in a high-organic-matter Mollisol

Simulación de cambios en el carbono orgánico del suelo con el modelo AMG en un Mollisol con elevado contenido de materia orgánica
Simulação de alterações no carbono orgânico do solo com o modelo AMG num Molisolo com elevado teor de matéria orgânica

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ABSTRACT

Soil organic carbon (SOC) management requires a precise knowledge of how it is affected by soil use. Simulation models could help for this purpose. The AMG model is simple, requires information that is easily available, and uses few parameters. This model has neither been calibrated/adjusted nor validated for loamy soils with high SOC concentrations. We hypothesized that AMG would satisfactorily simulate SOC stock changes in soils with these characteristics. The aims of this work were: 1) to adjust and validate AMG for different tillage systems, nitrogen (N) fertilization levels and crop types for loamy-high-SOC Mollisols, and 2) to simulate future SOC changes under different production scenarios. We used SOC stocks (0-20 cm depth) from three long-term experiments (1976-2012) (tillage systems, crop rotations, and N fertilization) in the Southeastern Buenos Aires Province, Argentina (37º 45' S, 58º 18' W) on a complex of Mollisols. Data from two of those experiments was split into two groups to adjust unknown model parameters and for cross validation. Data from the third experiment was used for independent validation. The model was used to simulate SOC stock variation (30 yr) under different combinations of initial SOC stocks (SOCi, three levels) and crop rotations (six rotations regarding continuous cropping and crop-pasture rotations). Model performance was evaluated through statistical indicators based on observed-simulated value differences, and simple linear regression of observed on simulated values. Cross validation yielded promising indicators with the mean observed-simulated value differences close to 0 ($P > 0.05$). Root mean square error (RMSE) and RMSE as percentage of the mean of observed values (RMSEp) were 6.0 Mg C ha^{-1} and 7.5%, respectively, which are acceptable. Simple linear regression of observed and simulated values was highly significant ($P < 0.01$) with intercept and slope not different from zero and one ($P > 0.05$), respectively, although R^2 was low. Indicators of model performance by groups of treatments were, in general, acceptable and did not show clear trends associated with any management type. However, model performance was poorer under no tillage (NT) and N fertilization probably because of little observed data available for that treatment factor combination. Validation with independent data confirmed that AMG simulated SOC change satisfactorily. Future scenario simulations showed that when the SOCi stock was high (close to SOC saturation), even rotations with high intensification and carbon input produced a SOC stock decrease. Conversely, when the SOCi stock was low (35% loss of SOC with respect to saturation) all scenarios led to a SOC stock increase. However, AMG failed to acceptably simulate the expected effect of pastures in the rotation. The AMG model satisfactorily simulated SOC stock changes due to different management techniques of soils with a loamy surface texture and high

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original SOC stock. Therefore, the model could be used as a tool to help management planning with an admissible simulation error (RMSEp ~6%).

RESUMEN

El manejo del carbono orgánico del suelo (SOC) requiere del conocimiento de cómo es afectado por su uso. Modelos de simulación podrían ayudar en esta tarea. El modelo AMG es simple, requiere información fácilmente disponible y se basa en pocos parámetros. Este modelo no ha sido calibrado ni validado para suelos de textura franca con elevado contenido de SOC. Nosotros hipotetizamos que AMG simulará satisfactoriamente los cambios en el SOC debidos al uso agrícola de suelos de tales características. Los objetivos fueron: 1) ajustar y validar AMG en diferentes condiciones de sistema de labranza, fertilización con nitrógeno (N) y tipos de cultivos para Mollisoles de textura superficial franca y elevado contenido de SOC, y 2) simular cambios futuros de SOC bajo diferentes escenarios de producción. Utilizamos los contenidos de SOC (0-20 cm) de tres experimentos de larga duración (1976-2012) de sistemas de labranza, rotaciones de cultivos y fertilización con N en el sudeste de la provincia de Buenos Aires, Argentina (37º 45' S, 58º 18' W) sobre un complejo de Mollisoles. Los datos de dos ellos fueron divididos en dos grupos al azar para ajustar algunos de los parámetros del modelo y para validación cruzada, respectivamente. Los datos del tercer experimento fueron utilizados para una validación independiente. El modelo fue usado para simular la variación del SOC (30 años) bajo diferentes combinaciones de contenido inicial de SOC (SOCi, tres niveles) y rotaciones de cultivos (seis rotaciones considerando agricultura continua y rotaciones cultivo-pastura). El desempeño del modelo fue evaluado a través de indicadores estadísticos basados en la diferencia observados-simulados y regresiones lineales simples de observados vs. simulados. La validación cruzada dio resultados prometedores con una media de observados-simulados cercana a 0 (P > 0,05). La raíz del cuadrado medio del error (RMSE) y el RMSE como porcentaje de la media de los valores observados (RMSEp) fueron 6,0 Mg C ha^{-1} y 7,5%, respectivamente, que son valores aceptables. La regresión lineal simple de observados vs. simulados fue altamente significativa (P < 0,01) con ordenada al origen igual a 0 y pendiente igual a 1 (P > 0,05), aunque el R^2 fue bajo. Los indicadores por grupos de tratamientos fueron, en general, aceptables y no mostraron tendencias asociadas a un manejo en particular. Sin embargo, el desempeño del modelo fue más pobre bajo siembra directa (NT) con fertilización con N, posiblemente debido a la poca información disponible para esa combinación de tratamientos. La validación con datos independientes confirmó el buen desempeño de AMG. Las simulaciones a futuro mostraron que cuando SOCi era alto (cercano a la saturación de SOC), aún las rotaciones con alta intensificación y aporte de carbono provocaron disminución del contenido de SOC. Por el contrario, cuando SOCi fue bajo (35% de pérdida del SOC a saturación) todos los escenarios condujeron a aumentar el SOC. Sin embargo, AMG no fue capaz de simular aceptablemente el efecto esperado de las pasturas en la rotación. El modelo AMG simuló satisfactoriamente los cambios en contenido de SOC debido a diferentes manejos del suelo con textura franca y elevado contenido original de SOC. Por lo tanto, el modelo podría ser utilizado como herramienta de apoyo a la planificación del manejo con un error admisible (RMSEp ~6%).

RESUMO

A gestão do carbono orgânico do solo (SOC) necessita de um conhecimento rigoroso de como o uso do solo a pode afetar . Com esse objetivo podem ser utilizados modelos de simulação. O modelo AMG é simples, requer informação facilmente disponível e baseia-se num reduzido número de parâmetros. Esse modelo não tem contudo sido calibrado/ajustado nem validado para solos argilosos com elevado nível de SOC. Neste estudo partiu-se da hipótese que o modelo AMG poderá simular satisfatoriamente as variações de SOC devidas ao uso agrícola em solos com essas características. Os objetivos foram: 1) ajustar e validar o AMG sob diferentes condições de sistema de preparação do solo, fertilização com azoto (N) e tipos de cultura para Molisolos com textura argilosa e elevado teor de SOC, e 2) simular variações futuras de SOC sob diferentes cenários de produção. Para as simulações utilizaram-se os teores de SOC (0-20 cm) de três ensaios de longa duração (1976-2012) com sistemas de preparação do solo, rotações de culturas e fertilização com N no sueste da provincia de Buenos Aires, Argentina (37º 45' S, 58º 18' W) sobre um complexo de Molisolos. Os dados provenientes de dois de esses ensaios foram divididos em dois grupos ao acaso para ajustar parâmetros do modelo e para a validação cruzada, respetivamente. Os dados do terceiro ensaio forma usados para validar o modelo. O modelo foi usado para simular a variação de SOC (30 anos) sob diferentes combinações de teor inicial de SOC (SOCi, três níveis) e rotações de culturas (seis rotações com agricultura continua e rotações cultura-pastagem). O desempenho do modelo foi avaliado mediante índices estatísticos baseados na diferença observados-simulados, e regressões lineares simples entre observados e simulados. A validação cruzada apresentou *resultados promissores com uma média da diferença entre observados e simulados próxima de 0 (P > 0,05). A raiz do quadrado médio do erro (RMSE) e o RMSE expresso como percentagem da média dos valores observados (RMSEp) foram 6,0 Mg C ha^{-1} e 7,5%, respetivamente, os quais são valores considerados aceitáveis. A regressão linear simples entre observados e simulados foi altamente significativa (P < 0,01) com um coeficiente linear da reta de regressão próximo de 0 e com um coeficiente angular da reta próximo de 1 (P > 0,05), apesar do valor de R^2 ser baixo. Os índices por grupos de tratamentos foram, em geral, aceitáveis e não mostraram tendências associadas a uma gestão em particular. Contudo, o desempenho do modelo foi mais pobre em condições de fertilização com NT e N, possivelmente devido à pouca informação disponível para essa combinação de tratamentos. A validação com dados independentes confirmou que o AMG simulou a alteração do SOC de forma satisfatória. Os cenários futuros mostraram que quando o nível de SOCi foi elevado (próximo a saturação de SOC), mesmo as rotações com elevada intensificação e aportes de carbono provocaram diminuição do conteúdo de SOC. Pelo contrário, quando SOCi foi baixo (35% de perdas do SOC a saturação) todos os cenários aumentaram o nível de SOC. No entanto, o AMG não simulou aceitavelmente o efeito das pastagens na rotação. O modelo AMG simulou satisfatoriamente as variações de SOC devido a diferentes gestões do solo com textura argilosa e elevado teor inicial de SOC. Como tal, o modelo poderia ser usado como ferramenta de apoio no planeamento da gestão com um erro considerado admissível (RMSEp ~6%).*

KEY WORDS
Modelling, organic matter simulation, cropping systems, tillage systems, crop rotations

PALABRAS CLAVE
Modelización, simulación de materia orgánica, sistemas de cultivo, sistemas de labranza, rotaciones de cultivos

PALAVRAS-CHAVE
Modelação, simulação de matéria orgânica, preparação do solo, sistemas de lavoura, rotação de culturas

1. Introduction

Organic matter is a key soil component (soil organic matter, SOM) that controls its productivity, environmental quality and social sustainability. Moreover, SOM defines agroecosystem sustainability and regulates soil resiliency after disturbances by cropping. Soil organic matter is directly involved in the soil's physical, chemical, and biological properties and its resistance to degradation (Reicosky et al. 2011). Transformation of carbon (C) from plant and animal tissue to soil organic carbon (SOC) converts the soil into a sink of atmospheric carbon dioxide (CO2), contributing to its reduction (Stockmann et al. 2013). Therefore, SOM defines soil functioning in the agroecosystem and influences most of its ecosystem services (Powlson et al. 2011). Soil organic matter is a complex of organic substances, whose dynamics are regulated by carbonated inputs and transformation processes (Stevenson and Cole 1999), which in turn are regulated by environmental constraints and management practices (Reicosky et al. 2011).

A careful management of SOC to reduce its loss and/or promote its accumulation requires a precise knowledge of how management and crops affect SOC dynamics under different environments. However, owing to the complex interactions among factors that influence SOC dynamics, prediction of the SOC stock change due to cropping is difficult. Mathematical models have been used to try to describe, explain and/or reproduce natural events as simply as possible. Even though models cannot take into account all the factors that interact in natural systems, they have been useful for understanding many of the processes involved (Jørgensen and Bendoricchio 2001a). Hence, simulation models arise as an important tool to predict consequences of agronomic decisions on SOC dynamics and therefore on system sustainability (Quiroga and Studdert 2015).

Simulation models are developed using empirical information generated in experiments (short- or long-term trials) carried out at specific sites, and then validated using different information than that used for their development (Jørgensen and Bendoricchio 2001b). However, when a model is to be used in other environments, it is imperative to both validate and calibrate it (Smith et al. 1997) in order to adjust its parameters and reduce the uncertainty of the simulations (Gupta et al. 2006).

Soil organic C simulation models used throughout the world differ in simplicity and precision (Smith et al. 1997). Model complexity is defined by the depiction detail of the SOC dynamics, the biological and physic-chemical processes taken into account, the number of parameters involved, the simulation time step considered, and the input information required. Complex and sophisticated simulation models may describe system processes with high precision. However, they generally demand much input information and use a high number of parameters and coefficients that must be calibrated/adjusted using empirical information not always available. Hence, the use of those models is restricted to trained users and require complicated calibration/adjustment. Using simulation models as tools to help management by farmers and/or consultants implies that they ought to be both simple and based on input information easily available (Studdert et al. 2011).

The AMG model (Andriulo et al. 1999) is simple, requires information easily available, and uses few parameters. It considers only three SOC compartments: the active fraction (that is affected by mineralization), the stable fraction (that is assumed to be not affected by mineralization or management), and C input through crop residues (that transforms into the active fraction when humified). Due to the few parameters it uses, calibration can be performed rapidly and easily if information is available. This confers a flexibility to the model that allows it to be used with acceptable confidence under different conditions. After calibration, AMG successfully simulated SOC stock changes under different environmental conditions (soil type, surface texture, initial SOM stock, mean annual rainfall and temperature, among others) (Andriulo et al. 1999; Piccolo et al. 2008; Saffih-Hdadi and Mary 2008; Milesi-Delaye et al. 2013; Irízar et al. 2015). However, AMG has neither been calibrated/adjusted nor validated for soils with a loamy surface texture and high original SOM stock such as those of the Southeastern Buenos Aires Province, Argentina (SEBA).

Given its simplicity, AMG could be used by farmers and/or consultants as a tool to help decide on management practices that lead to the preservation and/or increase of SOC stocks. Therefore, it is necessary to know whether AMG is able to simulate SOC stock changes under different managements for the SEBA. We hypothesized that AMG would satisfactorily simulate SOC stock changes in soils with loamy surface textures and a high original SOM stock. The aims of this work were: 1) to adjust the AMG model for different tillage systems, nitrogen (N) fertilization levels and types of crops using data generated in different long-term soil management experiments carried out at the SEBA; 2) to validate AMG for Mollisols of the SEBA; 3) to simulate future SOC changes in the long term at the SEBA under different production scenarios.

2. Materials and methods

2.1. Experimental site

Data were used from three long-term soil management experiments carried out in the experimental field of the *Unidad Integrada Balcarce*, Balcarce, Buenos Aires Province, Argentina (37º 45' S, 58º 18' W, 138 m over sea level) between 1976 and 2012. The experiments were set in a soil complex of Typic Argiudoll (Soil Survey Staff 2014) (Mar del Plata series (INTA 1979)) and Petrocalcic Argiudoll (Soil Survey Staff 2014) (Balcarce series, with petrocalcic horizon below 0.7 m depth (INTA 1979)). Clay, silt, sand and SOM concentrations of the soil complex surface horizon (0-20 cm depth) are 231, 340, 429, and 57.4 g kg^{-1}, respectively, and the texture class is loam (INTA 1979). The slope is less than 2% and therefore soil water erosion could be considered negligible. Climate is mesothermal sub-humid to humid (according to Thornthwaite) or temperate-humid without a dry season (according to Köppen). The median annual rainfall is 939 mm yr^{-1} and annual mean daily temperature is 13.9 °C (Agri-weather Station, Unidad Integrada Balcarce, located ~1000 m away from the experiments).

2.2. Experiment description

Information from three long term experiments was used:

1) "Continuous Cropping": carried out between 1984 and 1995 with 16 crop sequences including wheat (*Triticum aestivum* L.), soybean (*Glycine max* (L) Merr.), maize (*Zea mays* L.), and sunflower (*Helianthus annuus* L.) under conventional tillage (CT, moldboard plow, disk harrow, and field cultivator) and with and without N (WN and WON, respectively). The experiment was laid out with a randomized complete block design with a split-plot treatment arrangement and four replications. This experiment is thoroughly described in Studdert and Echeverría (2000).

2) "Crop-pasture Rotations": carried out between 1976 and 2006 with different combinations of periods under cropping (wheat, soybean, maize, sunflower, potato (*Solanum tuberosum* L.), and oat (*Avena sativa* L.) and vetch (*Vicia sativa* L) or red clover (*Trifolium pratense* L.) as green manures) with and without N (WN and WON, respectively), and periods under grass-based pastures. Between 1976 and 1993 the tillage system was CT and between 1994 and 2006 some treatments were under CT and some others under no-tillage (NT). The experiment was laid out with a randomized complete block design with a split-plot treatment arrangement and three replications. Additional information about this experiment between 1976 and 1993 can be found in Studdert et al. (1997). The phase between 1994 and 2003 has been described in Eiza et al. (2005). Between 2004 and 2006 treatments and tillage systems were the same as described by Eiza et al. (2005).

3) "Tillage systems": carried out between 1997 and 2012. Crop sequence was maize-sunflower-wheat under two tillage systems (CT and NT) and two N fertilization levels (WN and WON). The experiment was laid out with a randomized complete block design with a split-plot treatment arrangement and three replications. Additional details on these experiments can be seen in Diovisalvi et al. (2008).

Soil organic C concentration at 0-20 cm depth determined in the fall, was available for many of the years of each experiment: 1) "Continuous cropping": most of the years for the treatments WON and only since 1990 for the treatments WN; 2) "Crop-pasture Rotations": between 1976 and 1993, most of the years for the treatments WON and only since 1981 for the treatments with N, and between 1994 and 2006, all of the years under both fertilization treatments; 3)"Tillage System": data available from both fertilization situations and from samples taken in 1998, 2000, 2003, 2006, and 2012. Soil organic C concentration had been determined by wet combustion (oxidation with potassium dichromate and sulphuric acid) with maintenance of the reaction temperature (120 °C) for 90 min to assure complete oxidation (a variant of the Walkley-Black method, Schlichting et al. 1995). Concentration of SOC was converted to stock (Mg C ha^{-1}) using bulk density measured or estimated as described by Studdert et al. (2011). Briefly, bulk density was measured in all experimental units of experiment 3 ("Tillage Systems") and between 1997 and 2006, in all experimental units of experiment 2 ("Crop-pasture Rotations") through the method proposed by Doran and Mielke (1984). For the rest of the experimental units we used the mean measured bulk density (1.25 Mg m^{-3}).

2.3. Model description

The AMG model (Andriulo et al. 1999) simulates SOC stock variation with time, using a year time step. The model considers that SOC can be split in three compartments (**Figure 1**).

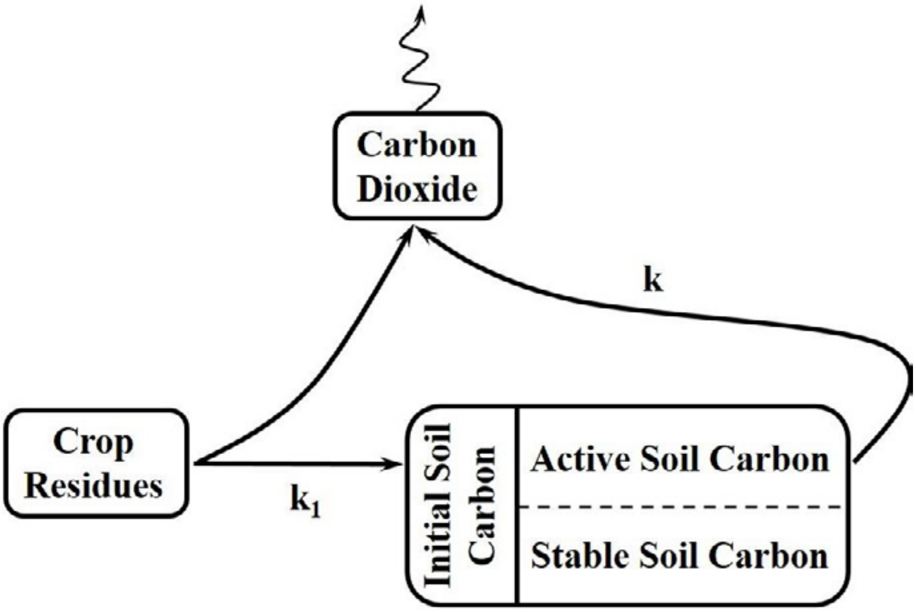

Figure 1. Diagram of AMG model (adapted from Andriulo et al. 1999). k_1: humification constant of fresh crop residues; k: annual mineralization coefficient of the active fraction of soil organic carbon.

Basic model equations are:

(Eq.1) $$SOC = SOCs + SOCa$$

(Eq.2) $$\delta SOC/\delta t = m \,.\, k_1 - k \; SOCa$$

where SOC is total SOC stock (Mg C ha^{-1}); SOCs is stable SOC stock (Mg C ha^{-1}) (Stable Soil Carbon in Figure 1) which is considered biologically inert or with an extremely low decay (Mg C ha^{-1}); SOCa is active SOC stock (Mg C ha^{-1}) (Active Soil Carbon in Figure 1); δSOC/δt is the partial derivative of SOC respect to time (Mg C ha^{-1} yr^{-1}); m is annual C input (Mg C ha^{-1} yr^{-1}) and represents all residues (below- and aboveground) left by crops (Crop Residues in Figure 1); k_1 is the humification coefficient (unitless); and k is the annual SOCa mineralization coefficient (yr^{-1}).

When C input is constant, Eq. 1 and 2 can be integrated as follows:

(Eq.3) $$SOCt = SOCs + (SOCi - SOCs)\, e^{-kt} + m\, k_1/k\, (1- e^{-kt})$$

where SOCt is total SOC at time t (Mg C ha^{-1}); SOCi is SOC stock at the beginning of simulation (Mg ha^{-1}) (Initial Soil Carbon in Figure 1); t is time (yr). In summary, the second term of equation (3) accounts for the decay of the active fraction of the old SOCa (i.e. that existing at the beginning of the simulation). On the other hand, the third term accounts for the incorporation of C to the active fraction due to humification of plan residues or new SOCa (i.e. the one that is incorporated from the beginning of the simulation until time t).

To calculate C input, wheat, soybean, sunflower and maize grain yields, potato tuber yield, and oat and vetch aboveground dry matter production, were used. The calculation of residue input mass by wheat, soybean, sunflower, maize, and potato, was done using the grain or tuber yield, and harvest indexes (HI) and the below- (root biomass + rhizodeposition)/ aboveground biomass (RB/TAB) relationship used by Studdert et al. (2011). For oat and vetch, RB/TAB was assumed the same as for wheat (Studdert et al. 2011). Pasture aboveground dry matter production was estimated as reported by Agnusdei et al. (2001) for similar pastures. Pasture RB/TAB was estimated according to

Bélanger et al. (1992). Carbon content of plan tissues was assumed as 0.43 kg C kg^{-1} (Sánchez et al. 1996).

The value of k under CT (0.07 yr^{-1}) was calculated according to Saffih-Hdadi and Mary (2008) using soil clay content and mean annual temperature (Agri-weather Station, *Unidad Integrada Balcarce*). We used the values of k_1 under CT proposed by Saffih-Hdadi and Mary (2008) for wheat and maize residues (0.21) and by Milesi-Delaye et al. (2013) for soybean residues (0.29). For potato (0.136), oat (0.21), oat+vetch (0.076), oat+red clover (0.076), and pastures (0.18) we used the values of k_1 under CT proposed by Ancelin et al. (2007). No values of k_1 were found in the literature for sunflower residues under CT and, therefore, it had to be adjusted.

Under NT values of both k and k_1 are lower than under CT (Andriulo et al. 1999; Mary and Wylleman 2001; Milesi-Delaye et al. 2013). No information was available about k and k_1 decrease under NT nor about SOCs in soils of the SEBA, and they had to be adjusted. The values of k and k_1 during the periods under pasture were assumed the same as under NT.

2.4. Adjustment

To adjust the unknown parameters in the model (**Equation 3**), we used observed SOC stocks at 0-20 m depth from “Continuous cropping” and “Crop-pasture Rotations” experiments. Data was split up in two groups: a) adjustment group, and b) validation group. The former was the largest with approximately 70% of all the data available (n = 1227 and n = 506 for adjustment and validation groups, respectively). The adjustment data group included data from three of the four blocks of the “Continuous Cropping” experiment (75% of the data) and the data from two of the three blocks of the “Crop-pasture Rotations” experiment (66% of the data). Data to include in the groups was randomly selected for each experiment, treatment and year.

The adjustment of the unknown parameters was done by using the Solver complement, Excel Program (Microsoft 2013), with the criterion of minimizing root mean square error (RMSE, Mg C ha^{-1}) over the execution of **Equation 3**, leaving the unknown parameters as adjusting variables one at a time. For SOCs stock adjustment, observed SOC stocks from crop sequences not including sunflower and under CT, were used. The starting point of the iterations was calculated from the average of the relations SOCs/SOCi reported by Andriulo et al. (1999) (0.66) and Saffih-Hdadi and Mary (2008) (0.65). Given the average of SOCi stock of “Continuous Cropping” (91.5 Mg C ha^{-1} in 1984, Studdert and Echeverría 2000) and “Crop-pasture Rotations” (94.3 Mg C ha^{-1} in 1976, Studdert et al. 1997) experiments was 92.9 Mg C ha^{-1}, the SOCs stock value used to start the iteration was 60.8 Mg C ha^{-1} (92.9 Mg C ha^{-1} * 0.655). For k_1 of sunflower residues, observed SOC stocks from crop sequences including sunflower under CT and estimated SOCs stock, were used. To start iterations, we used k_1 for soybean residues under CT (0.29, Milesi-Delaye et al. 2013). To adjust the changes in k and k_1 under NT, observed SOC stocks from the situations under NT, and estimated k_1 for sunflower residues under CT and SOCs stock, were used. The criteria followed for this adjustment was the proportion of reduction of k and k_1. To start the iterations, we used reductions of k and k_1 of 27 and 42%, respectively, as reported by Milesi-Delaye et al. (2013) for soils of the Northeastern Buenos Aires Province.

2.5. Model performance evaluation

The evaluation of the adjustment was done through “cross validation” using the validation data group. A second evaluation was done using all the data from the “Tillage Systems” experiment. This data had not been used for the parameter adjustment and, therefore, this validation result was totally independent from the adjustment.

Model performance evaluation was done through statistical indicators based on the difference between the observed and simulated SOC values. These statistical indicators were: mean of the differences between observed and simulated values (bias error, BE, Mg C ha^{-1}), mean of those differences relative to the observed values (bias relative error, BRE, %), root mean square variation (RMSV, Mg C ha^{-1}) (Kobayashi and Salam 2000) and RMSE expressed as stock (Mg C ha^{-1}) (Fox 1981) and as percentage respect to the mean of the observed SOC values (RMSEp, Smith et al. 1997). Root mean square variation represents error dispersion around its mean (BE) and RMSE represents error dispersion around zero. The comparison between RMSV and RMSE evaluates the magnitude of under- or overestimation of the model and the similarity between observed and simulated values.

Equality of BE and BRE to 0 was evaluated through t tests with an amalgamated error assuming a linear model describing changes in those indicators and the coefficient of determination (CD) (Loague and Green 1991) was calculated. This CD is a generalization of the coefficient of determination of a linear regression model (R^2) and may show values greater than 1. Values of CD close to 1 indicate that the variability of simulated values adequately describe the variability of the observed ones.

For the complementary independent validation (i.e. with data from the "Tillage Systems" experiment) the RMSE at 95% probability ($RMSE_{95\%}$; Mg C ha^{-1}) and the $RMSE_{95\%}$ relative to the mean observed value ($RMSEp_{95\%}$; %) (Smith et al. 1997), were calculated. The comparison of RMSE and RMSEp with $RMSE_{95\%}$ and $RMSEp_{95\%}$, respectively, shows whether simulated values are, on average, within the 95% confidence interval of observed SOC stocks.

Simple regression analyses between observed and simulated SOC values (Piñeiro et al. 2008) were performed. The joint hypothesis of equality of intercept and slope of each simple linear regression to 0 and 1 respectively was evaluated through F tests. All statistical analyses were performed with the R statistical package (R Core Team 2015).

2.6. Simulation of future scenarios

Eighteen different scenarios were defined to perform 30-yr simulations. Three SOCi were considered: 1) high (94.0 Mg C ha^{-1}): close to SOC stock of a pristine soil of the SEBA (Studdert et al. 1997; Studdert and Echeverría 2000; Sainz-Rozas et al. 2011), 2) medium (77.6 Mg C ha^{-1}): representing approximately 50% of SOC stock loss surveyed by Sainz-Rozas et al. (2011) in the SEBA and close to SOC stock assumed by Domínguez and Studdert (2006) as the minimum for soil functions, and 3) low (61.1 Mg C ha^{-1}): representing a 35% loss from pristine SOC stock (Sainz-Rozas et al. 2011). For each SOCi stock, six crop rotations with different indexes of sequence intensification (ISI, Caviglia and Andrade 2010) and/or different yield levels were regarded. All crops were assumed as cropped under NT. **Table 1** shows crop rotations and some of their agronomic characteristics.

Table 1. Crop rotation scenarios for 30-yr simulations with AMG. ID: crop rotation identification number; ISI: index of sequence intensification (%) (proportion of time occupied by living crops on a monthly basis, Caviglia and Andrade 2010); CI: mean annual carbon input (Mg C ha^{-1} yr^{-1}); Sb: soybean; M: maize; W: wheat; W/Sb: wheat and double-cropped soybean; Pp3: grass-based pasture for three years; Usual: yield level obtained by farmers with an average technology level; Improved: yield level obtained by farmers with high technology level

Crop rotation		Yield level	ISI	CI
ID	Rotation			
1)	Continuous Sb	Usual	45.8	2.48
2)	M-Sb-W	Usual	44.5	4.79
3)	M-Sb-W/Sb	Usual	56.9	5.17
4)	M-Sb-W/Sb (2)	Improved	56.9	6.80
5)	M-Sb-W-Pp3	Improved	70.8	7.18
6)	M-Sb-W/Sb-M-S-W-Pp3	Improved	65.3	6.89

Indexes of sequence intensification were expressed as the percentage of total time of simulation occupied by crops with living roots colonizing the depth of simulation (0-20 cm depth) (adapted from Novelli et al. 2011). Indexes of sequence intensification were calculated assuming that maize, soybean, wheat and wheat/double-cropped soybean had living roots occupying soil during 165, 165, 150, and 285 d, respectively. Usual yield (**Table 1**) was assumed as that obtained with average technology (neither completely balanced fertilization, nor completely effective pest, weed, and disease control): 9000, 2900, 6800, and 1750 kg grain ha^{-1} for maize, soybean, wheat and double-cropped soybean, respectively (Andrade, pers. comm.). Improved yield (**Table 1**) was assumed as that obtained with high technology (balanced fertilization, effective pest, weed, and disease control, supplementary irrigation, adequate cultivar, seed rate, row spacing, and planting/seeding rate): 13000, 3750, 8000, and 2200 kg grain ha^{-1} for maize, soybean, wheat and double-cropped soybean, respectively (Andrade, pers. comm.) and 14000 kg dry matter ha^{-1} for pastures (Marino, pers. comm.). For the first year of pastures it was assumed that living roots occupied soil for 300 d and for the second and third years, 360 d. Likewise, it was assumed that pastures were neither grazed nor harvested for hay and/or silage and therefore that all aboveground dry matter produced was returned to the soil. Carbon input produced by crops and pastures was estimated as indicated before. Effects linked to expected global climate change (i.e. atmospheric CO_2 concentration and air temperature increases) were not taken into account for simulations.

The AMG model was run for each SOCi-crop rotation combination using parameters from the literature and those adjusted as described above. In order to estimate an annual rate of SOC stock variation, simple linear regressions of simulated SOC stock vs. year were performed (R Core Team 2015). For all simulations, SOC stock at equilibrium (SOCe) was calculated as follows:

(Eq.4)	$SOCe = SOCs + m_m\, k_{1m} / k_m$

where m_m is mean annual C input (Mg C ha^{-1} yr^{-1}); k_{1m} is the mean humification coefficient (unitless); and km is the mean annual SOCa mineralization coefficient (yr^{-1}).

3. Results and discussion

3.1. Adjustment and cross validation

The value of k_1 under CT obtained for sunflower residues was 0.28. The adjusted value of SOCs was 60.4 Mg C ha^{-1}. The k and k_1 under NT represented 84% and 71% respectively, of those under CT.

Cross validation yielded promising statistical indicators when all the data was taken into consideration. Bias error (0.17 Mg C ha^{-1}) and BRE (-0.36%) were not significantly different from zero ($P > 0.05$) and RMSE, RMSV, and RMSEp were 6.0, 6.0 Mg C ha^{-1} and 7.5% respectively. These values are higher than those reported by Milesi-Delaye et al. (2013) and Irízar et al. (2015) for silty-loam soils, but within the range (6-10 Mg C ha^{-1} and 5-8 %) reported as acceptable (Smith et al. 1997). Simple linear regression between all observed and simulated values was highly significant ($P < 0.01$) and the joint hypothesis of intercept equal to 0 and slope equal to 1 could not be rejected ($P = 0.72$). Despite the R^2 being relatively low (0.40), linear regression showed that simulated SOC stocks acceptably reflected the variation in observed SOC stocks.

To evaluate model performance, data of the validation data group were re-grouped through the tillage system and N fertilization levels. **Table 2** shows the validation statistical indicators after re-grouping.

Table 2. Statistical indicators of AMG performance grouping data in the validation data group according to tillage system and nitrogen fertilization level. CT: conventional tillage; NT: no-tillage; WON: without nitrogen fertilizer; WN: with nitrogen fertilizer; BE: mean bias error (Mg C ha^{-1}); BRE: mean bias relative error (%); RMSE: root mean square error (Mg C ha^{-1}); RMSV: root mean square variation (Mg C ha^{-1}); RMSEp: relative RMSE (%); CD: coefficient of determination

Tillage system	Nitrogen fertilization	Number of observations	BE	BRE	RMSE	RMSV	RMSEp	CD
CT	WON	248	-0.5	-1.2*	6.3	6.3	7.8	0.3
	WN	144	0.5	0.02	6.3	6.3	7.8	0.3
NT	WON	62	1.5*	1.5	5.1	4.9	6.6	0.3
	WN	52	0.8	0.8	4.3	4.2	5.6	0.3

* significantly different from zero (P < 0.05).

In general, statistical indicators of model performance were adequate. There were no trends of under- or overestimation associated with any of the tillage system-N fertilization combinations. Equality of BE and BRE to 0 (only one case of each variable was significantly different (P < 0.05) from 0), and similarity between RMSE and RMSV as well as RMSEp values indicate good model performance (Smith et al. 1997). However, RMSE values (**Table 2**) were higher than those reported by Irízar et al. (2015) (below 2 Mg C ha^{-1}), for silty-loam soils of the Northeastern Buenos Aires Province. Coefficients of determination (Loague and Green 1991) were low (0.3, **Table 2**) indicating that only 30% of the variation of simulated values was explained by the variation in observed ones. Simple linear regression analysis results are shown in **Figure 2**.

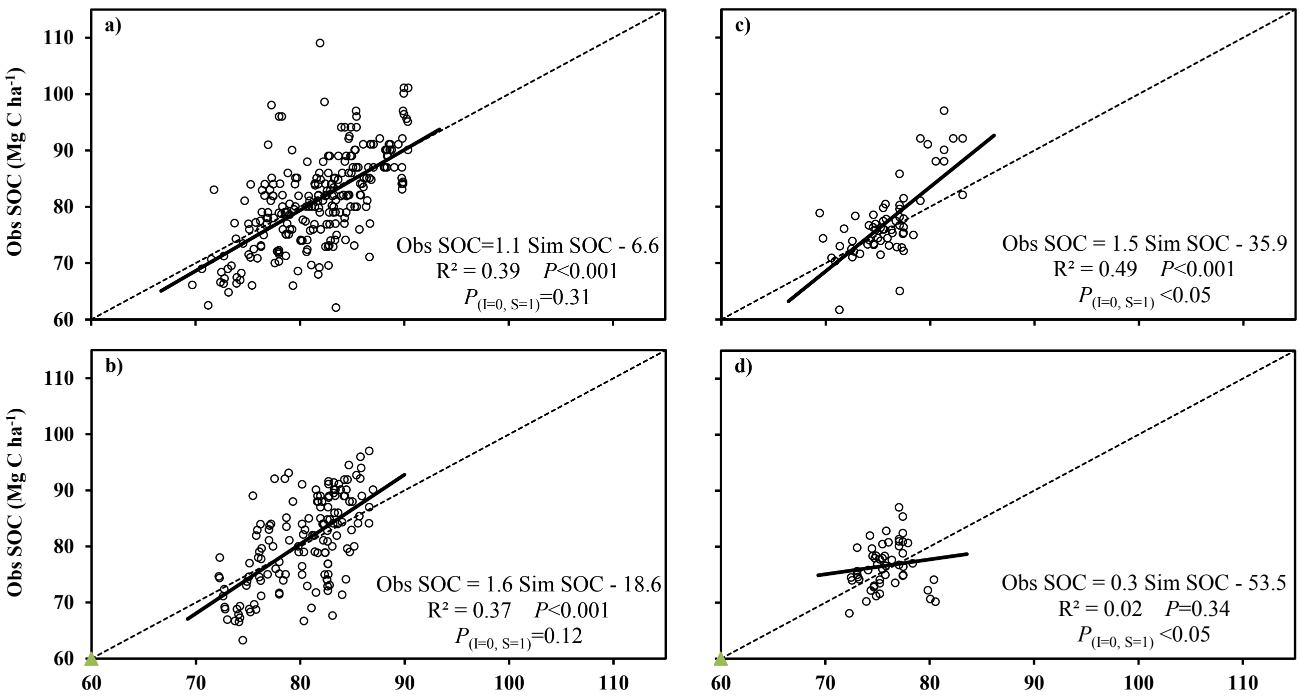

Figure 2. Simple linear regressions between observed soil organic carbon stocks (Obs SOC) and simulated soil organic carbon stocks (Sim SOC) of the validation data group under two tillage systems (conventional tillage (a, b), and no-tillage (c, d)) and two nitrogen fertilization levels (without nitrogen (a, c) and with nitrogen (b, d)). I: intercept; S: slope. The dotted line represents the 1:1 line.

Only the regression for NT-WN treatments was not significant ($P > 0.05$) (**Figure 2d**). On the other hand, the regression of observed vs. simulated SOC stocks under NT-WON (**Figure 2c**) was the only highly significant ($P < 0.01$) one for which the joint hypothesis of intercept equal to 0 and slope equal to 1, was rejected ($P < 0.05$). These results appear to indicate that model performance was not completely acceptable under NT, especially WN. It is worth recalling that situations under NT showed the least number of cases (**Table 3**).

Model performance evaluation showed acceptable statistical indicators both for all the data, and when the data was grouped by tillage system and N fertilization level (**Table 2**). Root mean square errors were mostly around or below 6 Mg C ha^{-1} and, in general, RMSEp were not higher than 8%, considered acceptable by Smith et al. (1997). However, for silty-loam soils of the Northeastern Buenos Aires Province under different crop sequences and tillage systems, Irízar et al. (2015) reported RMSE below 2 Mg C ha^{-1} and RMSEp between 0.7 and 4.1%, which were considerably lower than those obtained in our experiment (**Table 2**). Those authors and Milesi-Delaye et al. (2013) adjusted the value of SOCs for each treatment evaluated and this could have led to an improved model performance. Andriulo et al. (2012) indicated that AMG is very sensitive to SOCs. We used a unique SOCs stock since we understand that the most stable SOC fraction is not dependent on management (Six et al. 2002) unless it produced different soil erosion rates, which is not the case in our experiments. SOCs was not determined using the $^{13}C/^{14}C$ natural abundance method which is the most recommendable for determining SOCs (Andriulo et al. 2012), and this could have led to misleading simulations.

The statistical indicators show that the adjustment procedure of the unpublished parameters was, in general, adequate. Nevertheless, the observed vs. simulated linear regressions did not always show the same trend as the statistical indicators based on the difference in observed - simulated values. Linear regression with all data together was acceptable despite the low R^2. However, when treatments were grouped by the tillage system and N fertilization level (**Figure 2**), regressions were not always good.

The poorest regressions were under NT and especially for WN treatments, however, in our experiments ("Crop-pasture Rotations"), NT started after 18 yr of crop rotations under CT. Therefore, SOC stocks were low and with a relatively narrow range of variation (**Figure 2c, d**) especially in the treatments WN (**Figure 2d**). Errors in simulations could also have arisen from C input estimation (unique HI and RB/TAB for each crop, and using estimated pasture yields), the variability among replications of observed SOC values (Studdert et al. 1997; Studdert and Echeverría 2000), the narrowness of its range, the way some of the parameters were estimated (e.g. SOCs), among others. Validation with independent data would help to confirm the apparent good performance for high-SOM-concentration Mollisols of the SEBA,

3.2. Independent validation

Statistical indicators obtained in this validation, both in general and for each individual treatment of the "Tillage Systems" experiment, are shown in **Table 3**. Although CD was low, results for all data were as good as those observed for cross validation. Both BE and BRE were low and not statistically different from 0. Root mean square errors and RMSEp were within the range considered acceptable by Smith et al. (1997). On the other hand, RMSE and RMSEp were lower than $RMSE_{95\%}$ and $RMSEp_{95\%}$, respectively, indicating that simulated values were within the 95% probability confidence interval.

Statistical indicators for individual treatments were also acceptably good. All BE were below 5 Mg C ha^{-1} although two of them were statistically different ($P < 0.05$) from 0. Likewise, two BRE were statistically different ($P < 0.05$) from 0 and only one was slightly out of the ± 5% range (-5.68%, CT-WON, **Table 3**). Differences between RMSE and RMSV were relatively high in two cases (1.71 and 1.74 Mg C ha^{-1} for CT-WON and NT-WN, respectively). Root mean square errors and RMSEp were within or close to the range considered acceptable by Smith et al. (1997). All RMSE and RMSEp were lower than $RMSE_{95\%}$ and $RMSEp_{95\%}$, respectively, indicating that simulated values were acceptable. Only one CD was extremely low (CT-WN, **Table 3**), but two of them were close to 1 (CT-WON and NT-WN, **Table 3**) and the other (NT-WON, **Table 3**) was acceptable (0.59).

Table 3. Statistical indicators of AMG performance in an independent validation with data from the "Tillage Systems" experiment. Treat.: treatment; Num. obs: number of observations; BE: mean bias error (Mg C ha^{-1}); BRE: mean bias relative error (%); RMSE: root mean square error (Mg C ha^{-1}); RMSV: root mean square variation (Mg C ha^{-1}); RMSEp: relative RMSE (%); $RMSE_{95\%}$: RMSE at 95% probability (Mg C ha^{-1}); $RMSEp_{95\%}$: relative RMSE at 95% probability (%); CD: coefficient of determination; CT: conventional tillage; NT: no-tillage; WON: without nitrogen fertilization; WN: with nitrogen fertilization

Treat.	Num. obs.	BE	BRE	RMSE	RMSV	RMSEp	$RMSE_{95\%}$	$RMSEp_{95\%}$	CD
GENERAL	60	0.56	0.36	4.53	4.50	5.83	4.79	6.17	0.18
CT-WON	15	-3.92*	-5.68*	5.34	3.63	7.35	7.15	9.84	1.07
CT-WN	15	0.33	0.23	3.25	3.23	4.17	6.66	8.55	0.20
NT-WON	15	1.88	2.24	3.73	3.22	4.75	6.86	8.73	0.59
NT-WN	15	3.96*	4.67*	5.40	3.66	6.61	8.26	10.11	1.07

* significantly different from zero (P < 0.05).

Linear regression analyses were significant in most cases (P < 0.05 for four of them and P = 0.07 for the fifth, **Figure 3**), even though R^2 values were low (ranging 0.22-0.35 for individual treatments and 0.28 for all data together (**Figure 3**)). Intercept and slope of linear regression including all data (**Figure 3a**) and of two individual treatments (CT-WN (**Figure 3c**) and NT-WON (**Figure 3d**)) were jointly statistically equal (P > 0.05) to 0 and 1, respectively. All statistical indicators based on the differences observed - simulated values (**Table 3**) and of linear regressions observed vs simulated values (**Figure 3**) confirm the good performance

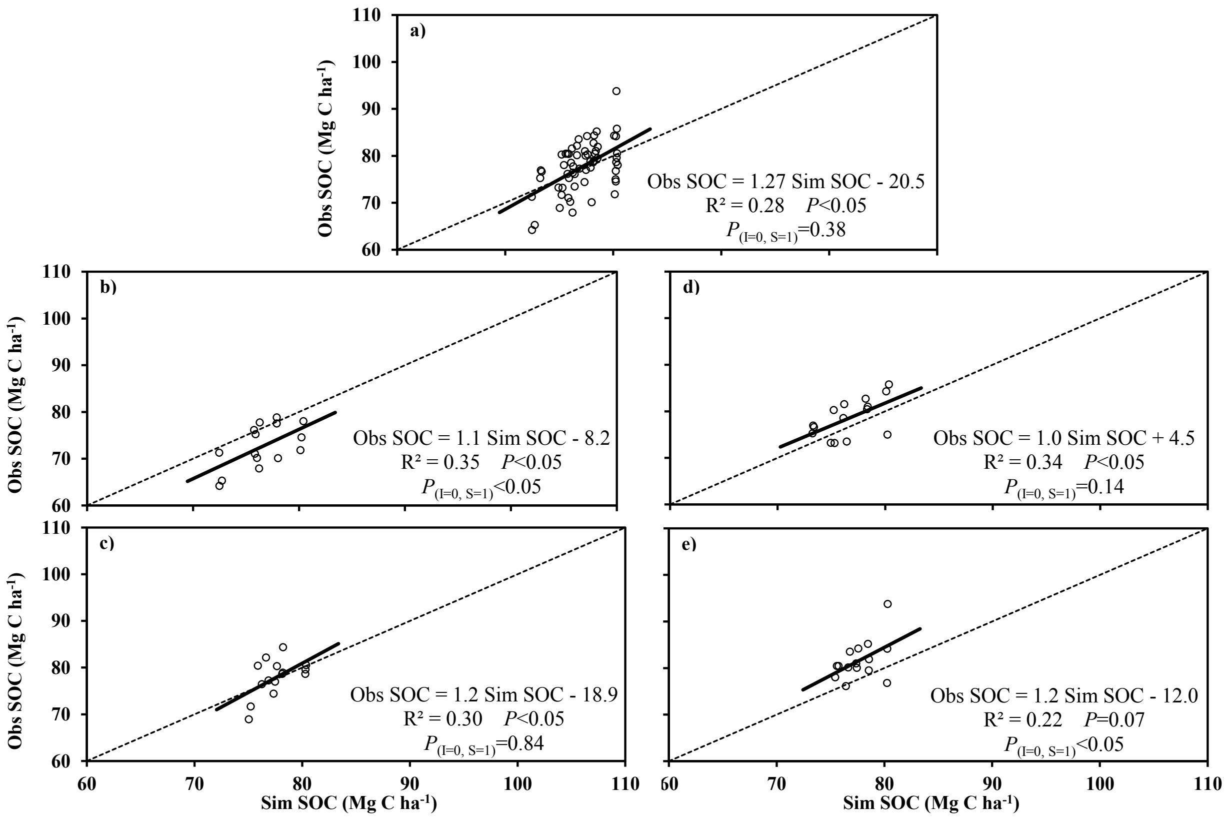

Figure 3. Simple linear regressions between observed soil organic carbon stocks (Obs SOC) and simulated soil organic carbon stocks (Sim SOC) of the "Tillage Systems" experiment (overall (a)) under two tillage systems (conventional tillage (b, c), and no-tillage (d, e)) and two nitrogen fertilization levels (without nitrogen (b, d) and with nitrogen (c, e)). I: intercept; S: slope. The dotted line represents the 1:1 line.

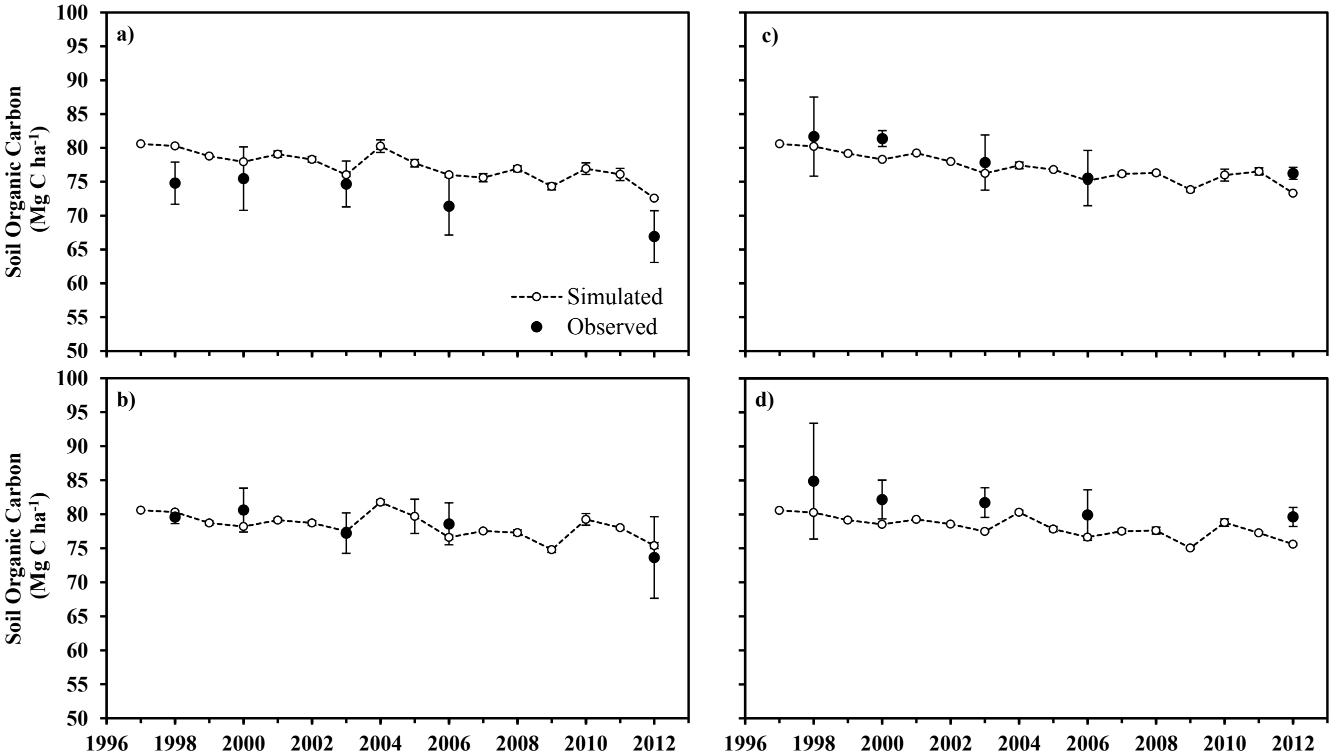

Figure 4. Observed and simulated soil organic carbon stocks as a function of time under two tillage systems (conventional tillage (a, b) and no-tillage (c, d)) and two nitrogen fertilization levels (without nitrogen (a, c) and with nitrogen (b, d)) for the "Tillage Systems" experiment. Vertical bars in each symbol indicate standard deviation.

of AMG for Mollisols of the SEBA with the adjusted parameters. Likewise, these results show no clear better or worse performance in relation to any N fertilization and tillage system combination.

Figure 4 shows simulated and observed SOC stocks vs. year for the "Tillage Systems" experiment. In all cases, simulated SOC stocks were close to mean observed ones. Standard deviations of observed values were always higher than those of simulated ones and in most cases the means of simulated values were within the variability range of the observed ones (Figure 4). Similar results were reported by Piccolo et al. (2008) for Oxisols of the Northeastern Argentina (Misiones Province) and Milesi-Delaye et al. (2013) for Mollisols of the Northeastern Buenos Aires Province.

In summary, even though some statistical results of cross validation were disappointing when grouped through management combinations (Table 2, Figure 2), independent validation (Table 3, Figures 3 and 4) confirmed the results of cross validation for all data together. Likewise, independent validation also showed no clear association of AMG performance with any management combination analyzed. Although for most cases of both cross (Table 2, Figure 2) and independent (Table 3, Figure 3) validations, CD and R^2 were low, the rest of statistical indicators of both validations were acceptable. This encourages the use of AMG as a valuable tool to simulate SOC stock changes for different managements with a mean relative error (RMSEp) of about 6%.

3.3. Simulation of future scenarios

Table 4 shows SOCe and SOC stock at the end of simulations of future scenarios, and the rate of variation obtained by simple linear regressions of simulated SOC vs. years. Comparing Tables 1 and 4, results of these simulations agreed in general with some other authors who worked with soils of the SEBA (Domínguez and Studdert 2006; Domínguez et al. 2009).

Table 4. Soil organic carbon stock at equilibrium (SOCe, Mg C ha^{-1}) and at the end of simulations with AMG (SOC_{30}, Mg C ha^{-1}), and slope of simple linear regression (Mg C ha^{-1} yr^{-1}). ID: crop rotation identification number; SOCi1: high initial soil organic carbon stock (94.0 Mg C ha^{-1}); SOCi2: medium initial soil organic carbon stock (77.6 Mg C ha^{-1}); SOCi3: low initial soil organic carbon stock (61.1 Mg C ha^{-1}); Sb: soybean; M: maize; W: wheat; W/Sb: wheat and double-cropped soybean; (2): higher yields; Pp3: grass-based pasture for three years

Crop rotation		SOCe	SOC_{30}			Slope		
ID	Rotation		SOCi1	SOCi2	SOCi3	SOCi1	SOCi2	SOCi3
1)	Continuous Sb	68.6	72.5	70.0	67.4	-0.66	-0.23	0.19
2)	M-Sb-W	73.3	76.7	74.1	71.6	-0.56	-0.13	0.29
3)	M-Sb-W/Sb	75.1	80.9	78.3	75.8	-0.50	-0.08	0.35
4)	M-Sb-W/Sb (2)	79.7	83.9	81.4	78.8	-0.40	0.02	0.45
5)	M-Sb-W-Pp3	78.3	81.1	78.6	76.0	-0.42	0.01	0.43
6)	M-Sb-W/Sb-M-S-W-Pp3	78.5	80.4	78.6	76.9	-0.44	-0.02	0.41

Domínguez and Studdert (2006) reported that an average C input of 3.8 Mg C ha^{-1} yr^{-1} led to an equilibrium of approximately 77.4 Mg C ha^{-1} (considered as the minimum value to grant an adequate soil functioning in the SEBA). Higher and lower C inputs would increase and decrease SOCe, respectively (Domínguez and Studdert 2006). However, our simulations showed that higher C inputs would be needed to reach SOCe even lower than the equilibrium level indicated by Domínguez and Studdert (2006) (rotations 2 and 3, Tables 1 and 4). This agrees with Domínguez et al. (2009) who showed that regardless of tillage system (CT or NT), C inputs between 5.5-6.0 Mg C ha^{-1} maintained SOC at approximately 78.0 Mg C ha^{-1} at 0-20 cm depth. Our simulations yielded that C inputs between 6.8 and 7.2 Mg C ha^{-1} (rotations 4-6, Table 1) would have led to SOCe between 78.3 and 79.7 Mg C ha^{-1} (Table 4).

When SOCi was high (SOCi1, Table 4), SOC stocks decreased in all rotations, even though the loss rate decreased with increasing C input. On the other hand, when SOCi was low (SOCi3, Table 4), SOC stocks increased in all simulations, with gain rates increasing with C input. However, when SOCi was medium (SOCi2, Table 4), mixed results were obtained: decreases in SOC stocks in rotations 1 and 2, and increases in rotations 3-6. In general, when expected SOCe was below SOCi, SOC losses would occur. Conversely, when expected SOCe was above SOCi, SOC increase would occur. This could be attributed to the degree of soil C storage capacity saturation (Six et al. 2002). High SOCi indicates C storage capacity is close to or at saturation and that SOCa is large. Estimated SOCs stock through the adjustment performed (60.4 Mg C ha^{-1}) represents ~64 and ~99% of high and low SOCi, respectively. When SOCi is low, only slight reductions of old SOCa (second term of Eq. 3) would occur. Therefore, even with low C input (rotation 1, Table 1), enough new SOCa (third term of Eq. 3) would be produced to overcome old SOCa decrease and lead to increase SOC stock. In contrast, when soil C storage capacity is close to saturation, a much higher C input would be needed to produce enough new SOCa to avoid SOC stock loss. Much higher C inputs would be needed to pursue higher SOCe. This could be achieved through even higher crop yields, increasing the frequency of high-residue-producing crops (e.g. maize), using organic manure, and/or intensifying crop sequence (i.e. increasing ISI: double cropping, using cover crops, including pastures in the rotation) (Caviglia and Andrade 2010; Quiroga and Studdert 2015).

However, even though rotations 5 and 6 had 24.4 and 14.8% higher ISI (5.6 and 1.3%), respectively, and greater C inputs than rotation 4 (Table 1), the SOCe expected with them were lower (Table 4). Figure 6 shows the evolution of simulated SOC stock for those rotations with all three SOCi. For soils of the SEBA, Studdert et al. (1997) demonstrated that SOC stock could be recovered by introducing a 3-yr grass-based pasture after 7 yr of conventional cropping. This is attributed to the continuous growing of dense and voluminous root systems together with the continuous aboveground biomass growth during most of pasture life, the reduction of tillage frequency, and the increase of time of soil occupation by living vegetation (i.e. increased ISI). Therefore, not only the C input/budget ratio is improved, but also its allocation in soil is enhanced (Follett 2001; Guzmán and Al-Kaisi 2010; Quiroga and Studdert 2015). This would occur particularly in the absence of grazing occurred (Franzluebbers 2010), as assumed in our simulations.

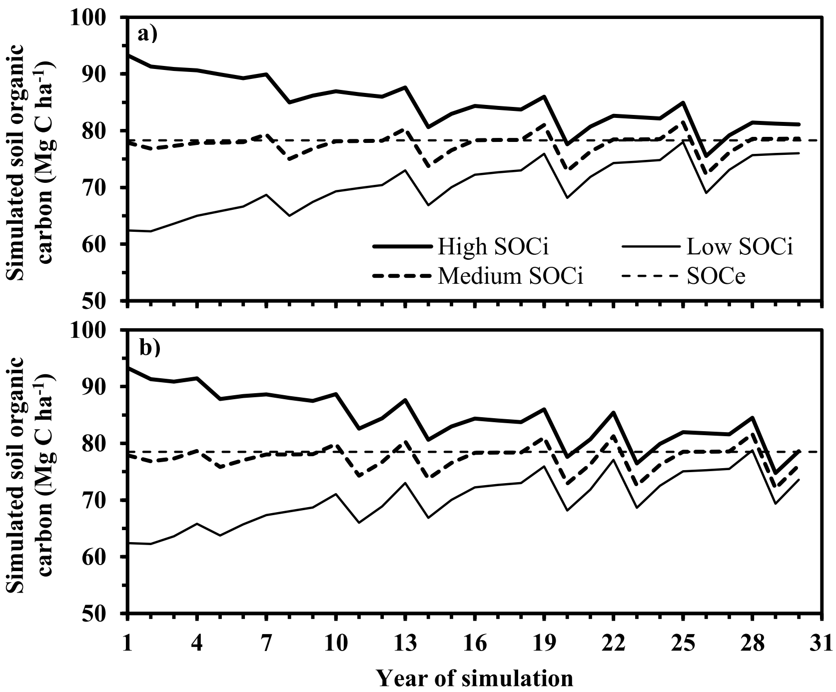

Figure 5. Simulated soil organic carbon with AMG as a function of year of simulation for two rotations (Rotations 5 (a) and 6 (b), **Tables 1 and 4**) and three initial soil organic carbon (SOCi) stocks: high (94.0 Mg C ha^{-1}), medium (77.6 Mg C ha^{-1}), and low (61.1 Mg C ha^{-1}). SOCe: soil organic carbon at equilibrium (**Table 4**).

The AMG model failed to simulate the expected effect of pasture when SOCi was high because a SOCe closer to SOCi could have been expected, especially for rotation 5 (**Table 4**). The simulation time step of AMG (one year) considers only total C input, but it does not reproduce how this input is distributed throughout the year. On the other hand, C provided from roots is responsible for much more SOC than C from aboveground residues (Kong and Six 2010), and the growth, distribution and residence time of pasture root systems are quite different from those of crops. In addition, C humification under pastures is likely to be higher than under crops. However, k_1 used for all AMG runs was 0.18 (Ancelin et al. 2007) which is lower than k_1 for soybean (0.29, Milesi-Delaye et al. 2013), wheat and maize (0.21, Saffih-Hdadi and Mary 2008), and sunflower (0.28). Probably, the RB/TAB relation assumed for pastures according to the literature (Bélanger et al. 1992) is somewhat inappropriate for the pastures used in this work since it was lower than that for grain crops with dense root systems (0.34 (pastures) vs. 0.43 (oats and wheat)).

4. Conclusions

With the information available, unknown parameters in the AMG model for loam-high-SOM soils could be easy and satisfactorily adjusted. Validation procedures performed (both cross and independent) showed acceptable performance of AMG with an admissible simulation error (RMSEp ~6%). As demonstrated for some other soils, AMG satisfactorily simulated SOC stock changes under different managements. Therefore, AMG appears to be an adequate tool to help management decisions also for loamy, high-SOM soils to pursue sustainable management. Its simplicity, the small amount of input information needed, and the fact that it can be run with simple computational tools (i.e. common spreadsheets), makes AMG very useful and feasible for use by producers and/or consultants without a special training.

However, results of validations and future scenarios simulations results suggest that further work needs to be done to confirm or adjust/ re-adjust some of the parameters in order to improve model performance. Stable SOC, k and k_1 without distinguishing different N fertilization situations, and k_1 and RB/TAB relation for grass-based pastures, require attention to reduce simulation error.

5. Ackowledgements

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