An Artificial Neural Network Approach for Predicting Soil Carbon Budget in Agroecosystems

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Soil quality has been associated with its organic matter content. Additionally, much effort has gone into understanding the C cycle and generating models suitable for C flux prediction. We used published data from long-term tillage experiments performed in the Pampas of Argentina, where CO_2–C emissions from organic C pools were determined in the field, for developing empirical models suitable for C flux emission prediction. We also performed 113 field experiments with corn (*Zea mays* L.), wheat (*Triticum aestivum* L.), and soybean [*Glycine max* (L.) Merr.] to determine crop C inputs to the soil. Two empirical modeling techniques were tested: polynomial regression and artificial neural networks. Both methodologies generated good models with R^2 ranging from 0.70 to 0.86. Nevertheless, neural networks performed better than regressions, with significantly lower RMSE values for both CO_2–C emissions and C input prediction. Daily CO_2–C emissions could be predicted by the neural network (R^2 = 0.86) using soil C content, temperature, and moisture level as independent variables. Crop C inputs (R^2 = 0.85) were estimated using crop type, yield, and rainfall during the growing cycle. The models were used for evaluating of the impact of soybean introduction in rotations during the 1970 to 1980 decade. Despite soybean C inputs to the soil being lower than those of wheat and corn, which were replaced in rotations, soil C budgets are similar compared with the 1970 to 1980 period, or changed from negative to positive at the present. These changes were associated with yield increases ascribed to technological improvement that resulted in greater C inputs from graminaceous crops.

Abbreviations: SR, sensitivity ratio.

Organic matter is a key factor in the determination of soil productivity (Sanchez et al., 2004) because it is the main reservoir of some nutrients like N for crops (Körschens et al., 1998). Additionally, it has beneficial effects on some physical properties that may impact crop growth (Gomez et al., 2001) and reduce erodibility, maintaining productivity in the long term (Nowak et al., 1985). Positive relationships have been detected between organic matter and yield at the regional scale (Alvarez, 2009) and estimations of yield decline due to the loss of organic matter have been made for some crops and areas of the world (Lal, 2004). Organic C and N have been considered as critical indicators of soil quality and included in soil quality indices (Bastida et al., 2008), not only due to their effects on productivity, but also because they act as substrate and an energy source for microorganisms, regulating the capacity of soils to degrade biological and chemical contaminants (Andrews et al., 2004).

The mass of C sequestered in soils is greater than the C mass in vegetation and atmospheric C together (Schimel et al., 2001). Agriculture has determined about one-third of the net flux of C from terrestrial ecosystems to the atmosphere during the last century due to soil C depletion and biomass destruction (Janzen, 2004), which represents a loss of 30 to 40 Mg soil C ha^{-1} contributing to global warming (Lal et al., 2007). Carbon sequestered in the soil depends on the climate (Alvarez and Lavado, 1998), vegetation (Jobbagy and Jackson, 2000), and soil texture (Buschiazzo et al., 1991). In wet climates, net primary productivity is greater than in dry climates, increasing the residue returned to the soil and the soil organic matter content. As ecosystem temperature increases, soil C decreases as a consequence of greater microbial activity and

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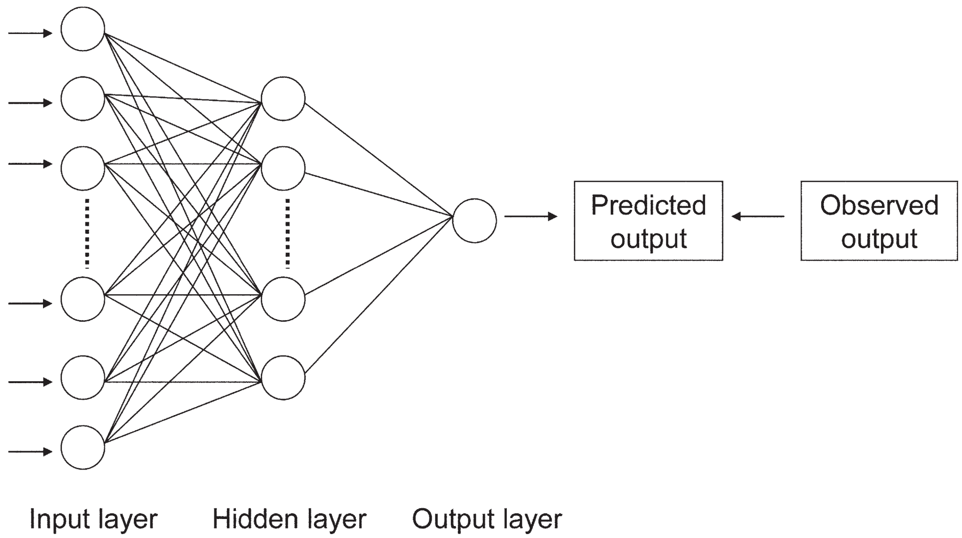

Fig. 1. Representation of a feed-forward artificial neural network showing neuronal layers and connections.

organic matter mineralization. Grasslands have greater C content than woodlands under similar climatic scenarios and fine-textured soils sequester more organic C than coarse soils. Cultural management also impacts the soil C sequestration potential. Strategies that lead to higher biomass production and C inputs to the soil, like rotation intensification (Hutchinson et al., 2007), fertilization (Alvarez, 2005), and irrigation (Lal et al., 2003) have a C sequestration potential in cropped soils. Strategies that reduce erosion and soil temperature, like conservation tillage systems, also produce an increase in soil C levels (Alvarez, 2005). Under adequate management practices, soils can recover between 50 and 70% of the C lost due to agricultural use, representing 0.4 to 0.8 Pg C yr^{-1} during the next 50 to 100 yr at the global scale (Lal, 2004), which can affect continental C balances.

Changes in soil C content are slow and difficult to detect (VandenBygaart and Angers, 2006), and long-term experiments are usually needed for studying its dynamics, with durations that may vary between 20 and 100 yr (Malhi et al., 2003; McGill et al., 1986). In some cases, after a period of 5 to 10 yr, the soil C changes produced by management can be detected (Grignani et al., 2007, Schjonning et al., 2007). Cropping use impact on C reservoirs cannot be determined for possible practices not tested in these long-term experiments and the results cannot be extrapolated to the future or at the regional scale (VandenBygaart and Angers, 2006). Process-based models are suitable tools for these purposes but their application is usually restricted by the information available for model parameterization and validation (Haefner, 2005). Simplistic models of soil organic C dynamics, like Roth-C (Jenkinson and Rayner, 1977), need information about crop yield and residue production, while the use of more sophisticated models that can simulate C dynamics at the ecosystem level, such as Century (Parton et al., 1993), may be restricted in developing countries by the lack of availability of quality information for the parameterization–validation process. An alternative for this information problem is the C budget technique, which has been applied to different ecosystems to study soil C dynamics (Andrén et al., 2001). Considering that C fluxes entering or leaving the soil are much greater than changes in the soil organic C content, this methodology allows determination of whether the soil is gaining or losing C in short time periods (Falgae et al., 2002; Rees et al., 2005). Changes in the soil C level between some tens of kilograms to megagrams per hectare may be detected in yearly time periods (Baker and Griffis, 2005; Verna et al., 2005). For soil C budget calculation, inputs and outputs of C to the soil are usually experimentally determined. When interest is focused on estimating changes in the soil C content under scenarios for which there are no available data on C fluxes, methods of predicting C inputs and outputs from the ecosystem must be developed by empirical modeling.

Artificial neural networks are empirical modeling techniques that have become popular in the biological sciences because they are more simple than process-based models and have a great predictive potential (Jørgensen and Bendoricchio, 2001; Özesmi et al., 2006). Their architecture and operation have been summarized previously (Alvarez, 2009). They have a structure and processing similar to the neural architecture and functioning of the brain, being data-driven tools capable of extracting information, like patterns or relationships, from data (Jørgensen and Bendoricchio, 2001). They do not assume an a priori structure for the data, are well suited for fitting nonlinear relationships and complex interactions, and can expose hidden relationships among input variables (Batchelor et al., 1997), but, as with other empirical models, they cannot extrapolate outside the range of data inputs. The most common artificial neural network structure is the multilayer perceptor with three neuronal layers: an input layer in which each neuron corresponds to an input variable, a hidden layer with a complexity that is empirically determined during the neural network fitting, and an output layer in which each neuron corresponds to an output variable (Fig. 1). Information flows from the input layer through the hidden layer and finally to the output layer, and the learning process, which is an iterative process, consists in fitting the weights associated with the transfer functions that couple neurons by comparing model outputs with experimental data (Jørgensen and Bendoricchio, 2001). The most common algorithm used to perform the learning process is back-propagation, which fits the weights from the output layer through the input layer (Kaul et al., 2005). Usually, a linear function is used to transfer information from the input layer to the hidden layer and a sigmoid function to transfer information from the hidden layer to the output layer (Kaul et al., 2005). Good results have been obtained using artificial neural networks as a modeling technique in soil science in areas as different as environmental correlation (Park and Vlek, 2002), soil organic C content prediction (Somaratne et al., 2005), fertilizer recommendation (Broner and Comstock 1997), and estimation of soil hydraulic properties (Nemes et al., 2003). These techniques have not yet been tested for soil C budget estimation.

The Pampas is considered to be one of the most suitable areas for grain crop production in the world (Satorre and Slafer, 1999). Wheat, corn, and soybean are the main crops (Ministerio de Agricultura, Ganadería y Pesca, 2010). During the 1970 to 1980 decade, soybean was introduced in pampean agroecosystems and now occupies around 60% of the cropped area (Ministerio de Agricultura, Ganadería y Pesca, 2010). Concern has increased in recent years about possible degradation effects of soybean on soils because of its low C input to the soil. Simulation models like Century have been used successfully for modeling the C dynamics of grassland soils (Alvarez, 2001; Piñeiro et al., 2006), but, at present, constraints encountered for model parameterization and validation in cropped soils have not yet been overcome, mainly because of the scarce information available on the soil cropping history in many pampean areas. Therefore, the use of empirical modeling techniques, like artificial neural networks, may be a suitable tool for soil C balance estimation in the region. Our objectives were (i) to test the ability of artificial neural networks for predicting the soil C budget by estimating CO_2–C emissions and crop C inputs to the soil, and (ii) to evaluate the impacts of the increase of soybean as a rotation component on the soil C budget of pampean soils.

MATERIALS AND METHODS

We tested the performance of regression methods and artificial neural networks for modeling soil C emission as CO_2–C and residue C inputs to the soil. Published results from seven field experiments in which soil respiration was assessed were used for CO_2–C emission modeling and 113 field experiments were performed, with wheat, corn, and soybean crops, to generate residue production and C input data. The best fitted models were then used for evaluating the soil C budget under the most common production scenarios found in the Pampas.

Study Area

The Pampas is a vast plain of around 50 Mha that runs from 28 to 40° S in Argentina. The relief is flat or slightly rolling, with Mollisols formed on loess-like materials as the predominant soils (Alvarez and Lavado, 1998). Its natural vegetation consists of grasslands in which graminaceous vegetation species are dominant. Around 60% of the area is devoted to agriculture. In the cropped portion of the region, the mean annual rainfall ranges from 600 mm in the west to 1200 mm in the east and the mean annual temperature from 14°C in the south to 20°C in the north. Agriculture is performed on well-drained soils, and areas with hydromorphic soils are devoted to pasture (Hall et al., 1992). Two important production subregions of the Pampas are the Rolling Pampa and the West Pampa. In the former, annual rainfall ranges between 900 and 1000 mm, the relief is slightly rolling, and the predominant soils are fine-textured, deep Argiudolls, with medium to high organic C contents. In the latter, rainfall varies between 700 and 900 mm, the relief is flat, and the most common soils are deep Hapludolls of coarse texture and low to medium organic C levels (Hall et al., 1992). In each subregion, four to five representatives counties were selected for the analysis: Arrecifes, Carmen de Areco, Chacabuco, Rojas, and Salto in the Rolling Pampa, and Carlos Tejedor, Gral Pinto, Rivadavia, and Gral Villegas in the West Pampa.

Data

Published results from long-term field experiments performed in the Pampas, in which CO_2–C emissions from soil organic reservoirs to the atmosphere were determined, were used for modeling (Table 1). Climate, soil, and management conditions varied widely between experiments, representing some common scenarios found in the region. All experiments had three to four plots for each management treatment where CO_2–C fluxes were determined by the inverted box method (Alvarez et al., 1998), usually at monthly intervals. In periods where intense crop root respiration was expected, respirometers that excluded crop roots from the inner soil were used (Alvarez et al., 1996). Three to six respirometers were installed in each plot and the results were averaged, generating one CO_2–C result for each treatment and sampling time, and generating an overall set of 188 data. The CO_2–C emitted by the soil was evaluated by titration (Alvarez et al., 1995a). The soil temperature at the 10-cm depth was determined by thermometers, and the soil water content in the 0- to 30-cm layer was determined gravimetrically at each respiration measurement date.

During 8 yr, 113 experiments were performed in the central portion of the Pampas in which biomass production and the yield of wheat, corn, and soybean were determined (Table 2). Experiments were installed within production fields and managed as commercial crops. Wheat experiments and methods of aboveground biomass and root collection in the 0- to 30-cm soil layer have been described in detail previously (Alvarez et al., 2004). Dried (70°C) plant material was ground and C determined by wet digestion (Amato, 1983). In the corn experiments, two treatments were contrasted, control and N fertilized, harvesting 10 microplots of 0.15 m^2 by treatment plot. Soybean experiments consisted in combinations of P and S rates, with different cultivars and three replicates for each treatment. Two 1-m^2 microplots were harvested by plot. The methods applied for corn and soybean were similar to those used for wheat, with the exception that soybean was harvested at two growing stages, R6.5 and R8. At the R6.5 stage, the maximum biomass is attained, before leaves drop but grains are not totally filled (Ritchie et al., 1989). At R8, all leaves have dropped and the crop is completely mature. Soybean aboveground total biomass was estimated as the sum of the

Table 1. Main characteristic of experiments in which soil respiration was determined.

Reference	Site	Soil†	Rotation‡	Tillage treatment§	Months with data	Plots	Data (n)	Clay + silt¶	Organic C¶	Soil temperature#	Rainfall††
					no.			%		°C	mm yr^{-1}
Alvarez et al. (1991)	Pergamino	TA	W/S- C	MP and NT	14	8	17	80.8	1.2– 1.4	20.0	780
Alvarez et al. (1995a)	Pergamino	TA	W/S	MP and DT	12	8	21	82.5	1.9– 2.0	18.4	1080
Alvarez et al. 1995b)	Pergamino	TA	W/S	MP and DT	12	8	24	82.5	1.9– 2.0	18.3	1220
Alvarez et al. (1996)	Pergamino	TA	W/S	DT and NT	12	6	26	80.3	1.0– 1.5	16.5	1240
Alvarez et al. (1998)	Pergamino	TA	W/S- C	MP and NT	12	8	24	84.0	2.0– 2.1	16.0	1100
Alvarez et al. (2001)	Junín	TH	W/S	MP and NT	2	6	14	41.4	2.1	16.7	1020
Bono et al. (2008)	Anguil	EH	O+HV-W-C-O	DP and NT	36	6	62	47.0	1.0– 1.1	16.4	830

† TA, Typic Argiudoll; TH, Typic Hapludoll; EH, Entic Haplustoll.

‡ W/S, double cropped wheat and soybean; C, corn; O+HV, oat + hairy vetch; W, wheat; O, oat.

§ MP, moldboard plow; DT, disk tillage with a harrow disk; DP, disk plow; NT, no-till.

¶ 0–20 cm.

Annual average at 10-cm depth during the period of soil respiration evaluation except for Alvarez et al. (2001), for which historic average is reported.

†† During the period of soil respiration evaluation except for Alvarez et al. (2001), for which historic average is reported.

biomass at R8 and the difference between the biomass at R8 and at R6.5. This difference was assumed to be mainly due to the fallen leaf biomass. Plot size ranged between 400 and 600 m^2. The results from plots under the same management treatment were averaged. The C input data set from all three crops had a size of 210. Rainfall was recorded during the crop growing cycles at all sites. Total root biomass to the 100-cm depth was estimated assuming that roots in the 0- to 30-cm layer accounted for 70% of the total belowground biomass (Jackson et al., 1996). Rhizodeposition, defined as root-derived C remaining in the soil at harvest by crops, originating from decomposition of dead roots, exudates, and sloughed root cells, was estimated to be 5% of the plant biomass (Swinnen et al., 1994; Kisselle et al., 2001). The total belowground C input was calculated as the sum of C in roots and rhizodeposition. The sum of above- and belowground C inputs were taken as the observed inputs for the analysis. Weed biomass and C content were also determined, when present, by methodologies similar to those described for the crops.

Modeling Techniques

Two modeling techniques were contrasted, polynomial regression and artificial neural networks. Data were randomly partitioned into two sets, 70% for training and 30% for validation; models were fitted using the training set and then tested on the validation set to determine their generalization ability. Training and validation sets used for regression fitting were also used for network models development.

A quadratic polynomial response model was tested that incorporated linear and quadratic terms for assessing linear and nonlinear effects of independent variables on the dependent variable and interaction terms between independent variables (Colwell, 1994). Fitting methods were applied as described elsewhere (Alvarez, 2009). Briefly, forward stepwise selection of independent variables was performed, testing co-linearity by the variance inflation factor (Neter et al., 1990). Categorical variables were encoded (0 or 1) testing only linear and interaction terms. Terms were maintained in the final models only if they were significant at $P = 0.05$. Feed-forward artificial neural networks developed by a supervised learning procedure, using the back-propagation algorithm for weight fitting, were tested for modeling (Rogers and Dowla, 1994). Network architecture definition, transfer functions, scaling methods, learning rate, and epoch size were similar to those described in Alvarez (2009). Maximum simplification of the network architecture was determined by using as few input variables and neurons in the hidden layers as possible without reducing the coefficients of determination (R^2). Input selection was performed by the classical stepwise procedure because of its simplicity compared with other possible techniques (Gevrey et al., 2003). Data for training were at least five times the connections in the networks to prevent overlearning (Gupta et al., 2003). Cross-validation was also used to avoid overlearning (Özesmi et al., 2006); the weight adjustment was stopped when R^2 from the validation set became lower than from the training set (Park and Vlek, 2002).

Available independent-input variables tested for modeling the CO_2–C flux were soil temperature, soil water content, clay, silt, organic C, and tillage treatment as a categorical variable. This information was extracted from the studies listed in Table 1. The C input from the crops was modeled as a function of crop type, attained yield, and rainfall during different periods in the growth cycle; this information was available for all the experiments. Crop type was taken as a nominal variable and encoded (1.0.0, 0.1.0, or 0.0.1) for neural network fitting (Brouwer, 2004). During the development of regression models, the average harvest index of each crop was used instead of a categorical variable strategy because it allowed better fits. Sensitivity analysis was performed to weight the effect of different inputs on CO_2–C emissions and crop C inputs by calculating a sensitivity ratio (SR) (Miao et al., 2006). The highest SR ratio implies the greatest impact of the analyzed input on the output. Neural networks were fitted using Statistica (Statsoft Inc., Tulsa, OK).

The R^2 values of the training and validation data sets were compared by a specific test using Fisher's Z transformation (Kleinbaum and Kupper, 1979), while RMSEs of the models developed by regression techniques and neural networks were contrasted by an F test (Snedecor and Cochran, 1967). Intercepts and slopes of the observed data regressed against the estimated data were contrasted with zero and one, respectively, using IRENE (Fila et al., 2003). In all cases, P was 0.05.

Table 2. Some characteristics from experiments in which C inputs were determined.

Crop	Variable	Years	Experiments	Data (n)	Rainfall†	Yield‡	Harvest index§	C input
		no.			mm	Mg ha^{-1}		Mg ha^{-1}
Corn	Mean range	3	35	70	687 (542–899)	11.17 (5.48–17.26)	0.51 (0.43–0.60)	5.38 (2.89–9.55)
Wheat	Mean range	2	58	58	302 (217–507)	4.46 (2.45–7.44)	0.36 (0.22–0.50)	4.02 (1.41–8.09)
Soybean	Mean range	2	20	82	534 (385–753)	3.93 (2.58–5.55)	0.43 (0.26–0.60)	2.60 (1.44–4.78)

† During the crop growing cycle.

‡ Yield with 14% water.

§ Grain dry matter/aboveground biomass dry matter.

Soil Carbon Budget

The soil C budget was calculated on an annual basis as the difference between C inputs and CO_2–C fluxes from the soil. Carbon inputs were the sum of crop inputs and other inputs produced by wild vegetation. Both CO_2–C fluxes and crop C inputs were estimated using the best models fitted previously. Inputs from wild vegetation were estimated by an independent approach outlined below. Carbon budgets were estimated for soils of the Rolling Pampa and West Pampa, where the majority of the experiments reported here were performed.

For CO_2–C flux estimation at an areal scale, we averaged values of organic C, using soil maps (Instituto Nacional de Tecnología Agropecuaria, 1989) and a procedure previously described (Alvarez and Lavado, 1998). Briefly, soil C concentrations reported in soil surveys were averaged, taking into account their corresponding areas and bulk densities, to obtain a weighted mean representative of each pampean subregion. Daily evolution of soil temperature and water content were estimated by splines (Bono et al., 2008), using available data from field experiments in which different rotations, fertilization strategies, and tillage systems were contrasted (data not presented). Annual C fluxes were estimated by integrating daily fluxes.

Estimations of C inputs from crops with time were performed on the basis of historic statistics of the seeded area and yield of corn, wheat, and soybean at the county level (Ministerio de Agricultura, Ganadería y Pesca, 2010). Using yearly seeded crop areas, the composition of the main rotations was established between the 1970 to 1980 decade and the present. Rainfall during the crop growing cycles was estimated by climatic records available from the Servicio Meteorológico Nacional (www.smn.gov.ar; verified 13 Mar. 2011). Estimations before 1970 were not performed because the crop harvest index changed, especially for wheat (Calderini et al., 1999), which might have affected the quality of the estimations. Rotations applied, yields, and rainfall information were used for biomass prediction by modeling C inputs with the developed empirical models.

Biomass production of wild vegetation grown during periods between crop growing cycles has not been assessed for the Pampas. In some rotations, in which these time periods may last 6 to 8 mo, an important input of C to the soil may be produced by this biomass because bare fallow periods are usually short, around 2 mo before crop seeding. We used the Century grassland model for an estimation of these inputs. A model version parameterized for simulating pampean grasslands was used with 10-d time steps (Alvarez, 2001). Wild vegetation biomass production and C input to the soil was estimated with the model for time spans between crops under the assumption that fallow periods were, in all cases, 2 mo. During these 2 mo of fallow, no biomass was produced due to soil clearing by tillage or herbicide use.

RESULTS

A broad range of variation of soil properties and crop yields was observed in the experiments (Tables 1 and 2). Soils varied from coarse textures, with 47% clay + silt, to finer ones, with around 80% clay + silt. Organic C content varied accordingly from 1% to approximately 2%. Yields differed two- or threefold between low and high values for all the crops studied, which was associated, mainly, with rainfall variability during the growing seasons. Management conditions were also different between experiments, with different rotations and tillage systems.

Emission of daily CO_2–C from organic soil reservoirs could be well predicted by the best models adjusted using the soil C mass content in the 0- to 50-cm layer, soil temperature at the 10-cm depth, and the water content in the 0- to 30-cm layer as independent variables or inputs. Both modeling techniques performed a good job for predicting soil CO_2–C emissions, but a better performance was attained using the neural network model (Fig. 2). The R^2 values ranged from 0.70 to 0.86 without significant differences between the training and validation sets, showing the ability of the fitted models for generalization to data not used in their construction. The intercepts and slopes of the predicted vs. observed data were not different from zero and one with the training or validation sets in all cases. The network with the highest R^2 had five neurons in the hidden layer and had a significantly lower RMSE in the training and validation sets than the best regression model. Soil CO_2–C flux increased as soil C content rose and was strongly affected by temperature, water content, and their positive interaction, so the nature of the process could be better described by the network approach than by the linear modeling technique. The SR indicated that temperature was the input with the greatest influence on CO_2–C emission (SR = 2.61), followed by soil C (SR = 2.20) and water content (SR = 1.35).

Carbon inputs from the crops to the soil could be well modeled by the two techniques, attaining R^2 from 0.70 to 0.85 (Fig. 3). No significant differences were detected between the R^2 of training and validation sets, with intercepts and slopes no different from zero and one, respectively. The best fitted neural network had four neurons in the hidden layer and a significantly lower RMSE, both in the training and in the validation data sets, than those of the regression, showing a better ability for predicting C inputs.

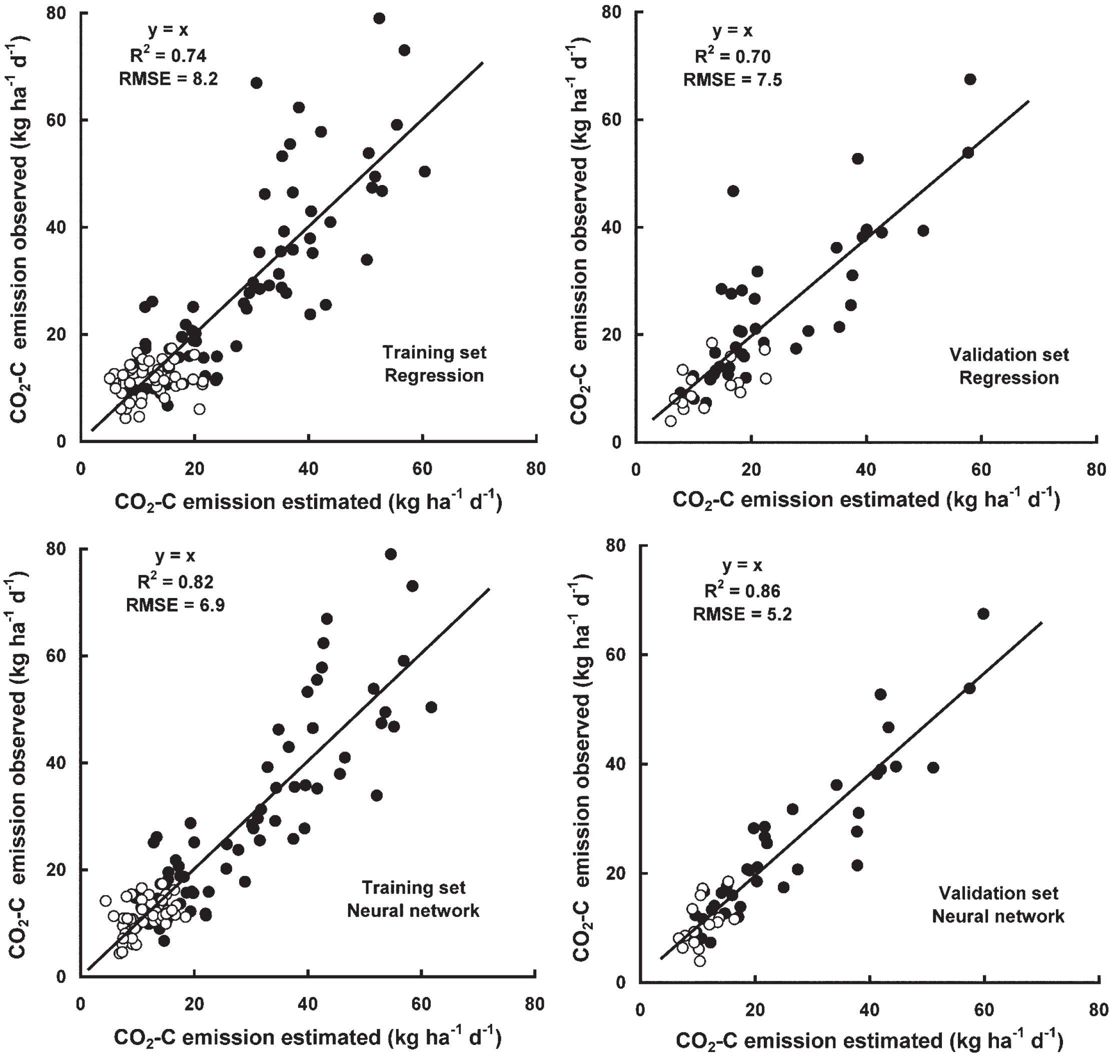

Fig. 2. Observed vs. predicted CO_2–C emissions estimated by polynomial regression or an artificial neural network approach for training and validation data sets. Empty circles: Haplustolls; full circles: Argiudolls and Hapludolls. Lines represent the fitted regressions.

Independent variables with significant effects on C inputs in the regression model were the average harvest index of each crop, yield, and rainfall during the entire growing cycle. The best network developed used as inputs crop type, yield, and rainfall during the growing cycle. Sensitivity analysis showed a greater effect of yield (SR = 2.73) than rainfall (SR = 2.10) and type of crop (SR = 2.04) on C inputs. Carbon inputs were linearly related to crop yield but with a great scatter of data because the harvest index was very variable, especially for wheat and soybean; these changes in the harvest index were affected by the interaction between yield and rainfall.

The network model developed for CO_2–C prediction was used for estimating the annual fluxes of C emitted by representative soils of the West and Rolling Pampa subregions under average climatic conditions. Carbon flux from soils of the Rolling Pampa was around 60% higher than from soils of the West Pampa, averaging 7.45 and 4.98 Mg C ha^{-1} yr^{-1}, respectively. Consequently, greater C inputs are needed in the Rolling Pampa than in the West Pampa to counteract CO_2–C losses and maintain soil C levels.

The crop sequence during the cropping phase of the rotations varied in the two pampean subregions from scenarios where corn and wheat were the predominant crops to the present situation in which soybean is the main crop (Table 3). This process was accompanied by a strong increase in crop yield, especially of graminaceous crops, which doubled or more in a 30-yr period (Table 3). As a consequence of this yield increase, the estimated crop C inputs from the entire rotation also increased (Table 4). In the West Pampa, estimated C inputs are around 44% higher now than in the 1970 decade; meanwhile, in the Rolling Pampa, the increase was about 14%. Carbon inputs were not linearly related to crop yield and were also affected by the interaction between climatic conditions during development and yield.

Biomass production from weeds developed during the crop growing seasons was null in the wheat and soybean experiments but ranged from 0 to 2.5 Mg C ha^{-1} in the corn experiments, with an average input of 0.5 Mg C ha^{-1} yr^{-1}. It was produced by weeds that grew during the last stages of the corn growing cycle, mainly *Cynodon dactilon* L. and *Tagetes minuta* L.

Biomass production of wild vegetation in the time span between crops, estimated by Century, ranged from 0.5 to 2 Mg C ha^{-1} yr^{-1} (Table 4). It was equivalent to 37% of the inputs from the crops as a mean. Taking into account the sum of inputs from crops, estimated by the neural network model, inputs

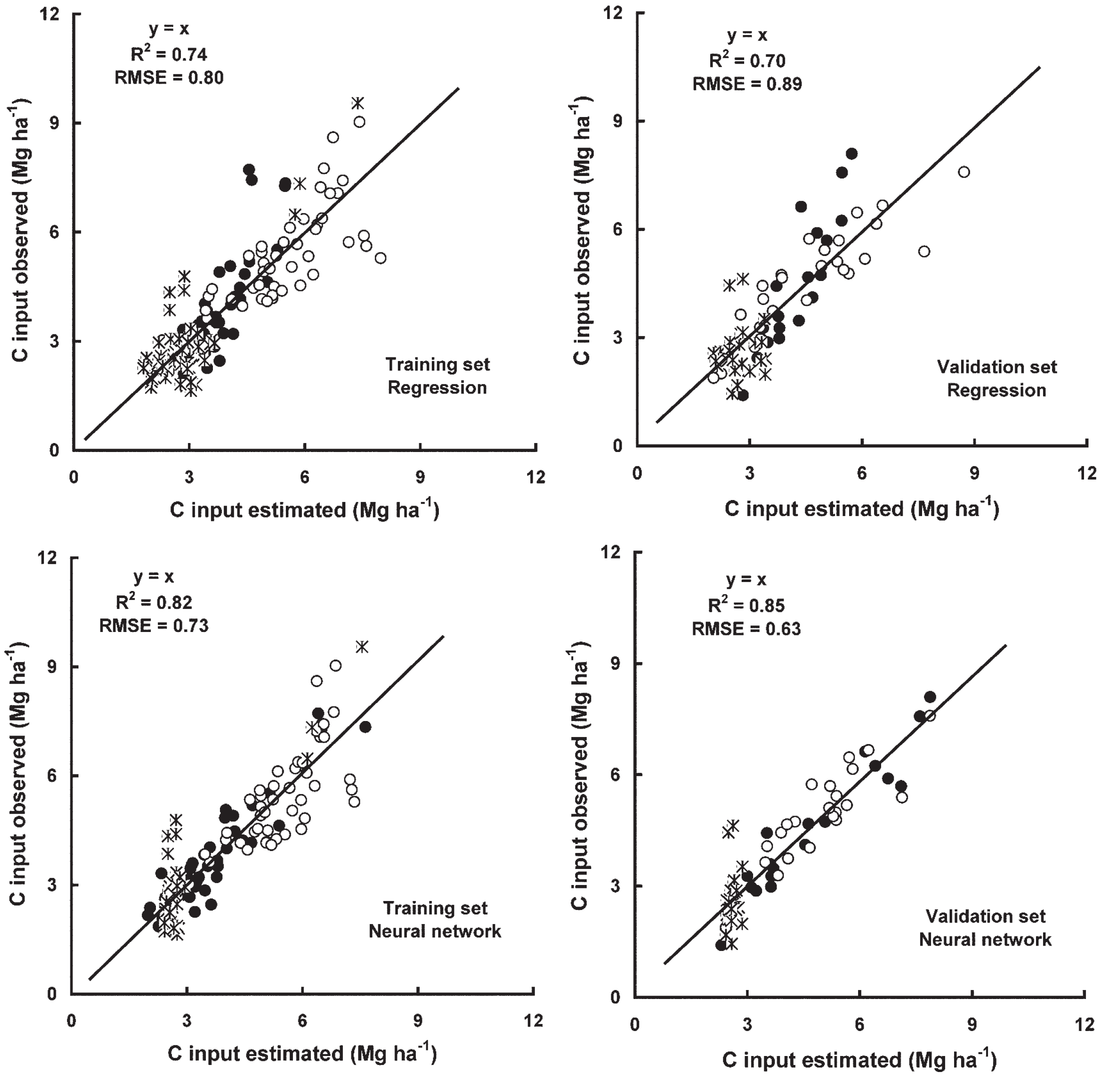

Fig. 3. Observed vs. predicted C inputs from crops estimated by polynomial regression and an artificial neural network approach for training and validation data sets. Empty circles: corn; filled circles: wheat; asterisks: soybean. Lines represent the fitted regressions.

from weeds developed during the corn growing season, and inputs from wild vegetation developed in time spans between crops, estimated by Century, the total C inputs to the soil during the rotations were recalculated (Table 4). Total input tended to increase from the 1970 decade to the present, averaging now around 5 Mg C ha^{-1} yr^{-1} in both the West and the Rolling Pampas.

The estimated soil C budget was negative in both pampean subregions in the 1970 decade (Table 4). As C inputs increased, the budget became positive in the West Pampa, but in the Rolling Pampa, it is still negative. In spite of the introduction of soybean in rotations and its low C inputs, soils are apparently not losing more C than 30 yr ago during the cropping phase of rotations as the result of the compensation effects of crop biomass production increases by technological improvements.

DISCUSSION

The artificial neural networks developed in this research fitted the data better than linear models, which can be ascribed to the nonlinear modality of responses and to the complex interaction between input variables (Gupta et al., 2003). The size of the data set and complexity of network architecture were adequate because cross-validation showed the ability of the models developed to generalize predictions. When available data for training are scarce (Broner and Comstock, 1997), too many input variables are used (Özesmi et al., 2006), or the number of neurons in the hidden layer is very high (Rogers and Dowla, 1994), network models tend to overlearn. Despite complex models possibly reaching greater R^2 values (Nemes et al., 2003), in some cases simpler ones allow better predictions (Lee et al., 2003), and an equilibrium must be attained between complexity and prediction capacity (Özesmi et al., 2006). The neural networks fitted here were simple models, being the effects of input variables in accordance with theoretical expectations. Sensitivity analysis quantified the impact of each input on the process involved, indicating a strong influence of the inputs selected on soil CO_2–C emissions and crop C inputs to the soil, as the SR were much higher than one in all cases (Miao et al., 2006). Despite their better prediction ability, neural networks could not be used for assessing the error associated with estimates at new values, which can be performed using regression methods.

Table 3. Most common rotations used and average yields in the Rolling and West Pampas.

Region	Time period	Rotation†	Crop yield			
			Wheat	Soybean‡	Corn	Soybean§
			kg ha^{-1}			
Rolling Pampa	1973–1976	C–C–C–C–W	1800	1530	3530	–
	1983–1986	W/S–C	1900	2430	4390	–
	1993–1996	W/S–C–S	2600	1670	5500	2390
	2003–2006	W/S–C–S–S–S	3640	2500	7960	3570
West Pampa	1973–1976	C–W–W	1790	1270	3050	–
	1983–1986	W/S–C–W–C–W	2000	1660	4110	–
	1993–1996	W/S–C	2390	1440	4500	–
	2003–2006	W/S–C–S–S	3370	2430	8430	3470

† C, corn; W, wheat; W/S, double cropped wheat and soybean; S, soybean.
‡ In the double cropped wheat/soybean sequence.
§ As the only crop in a year.

The determination of the CO_2–C flux evolved from the soil by microbial respiration is a precise method for quantification of C losses when estimating a soil C budget (Nay and Bormann, 2000). If live plant roots are present in the soil, CO_2–C emissions must be partitioned into autotrophic and heterotrophic respiration to evaluate only the CO_2–C flux generated from the organic soil reservoirs (Koizumi et al., 1993). Different methods have been used for empirical modeling of soil CO_2–C emissions. The results related to the effects of temperature and rainfall on total soil respiration from many ecosystems worldwide have been integrated (Raich and Schlesinger, 1992). Soil respiration increases as temperature and rainfall increase, a consequence of higher microbiological activity under warmer conditions and greater levels of soil residues and organic matter under wetter climates and higher C inputs. Modeling soil respiration as a function of temperature and water content allowed the development of models that can explain between 40 and 90% of its variation, depending on the ecosystem (Liu et al., 2008; Wang et al., 2008). Including variables in models that are related to plant biomass, like foliar area index (Amos et al., 2005) or net primary productivity (Han et al., 2007), may improve model performance. When total soil respiration is assessed, the inclusion of these types of variables in models may be the consequence of the impact of root respiration on CO_2–C flux (Casadesus et al., 2007). Also, variables that quantify the C substrate available for microorganisms, and regulate heterotrophic respiration, improve models. Some of these variables are soil organic C content (Reichstein and Beer, 2008) and residue mass present or added to the soil (Bono et al., 2008). In agroecosystems, excluding root respiration, between 40 and 50% of soil CO_2–C emission variation was explained using soil temperature and water content as independent variables in models fitted to respiration data from cropped or bare soil (Takata et al., 2008). Our network model may explain 86% of the variation of CO_2–C emissions from different soils, cropping management conditions, and years using only temperature, water content, and soil organic C as inputs. As a result of the simplicity of the model, it may be applied to many pampean agroecosystems for which this information is available.

Annual fluxes of CO_2–C from soils to the atmosphere range between 0.6 to 26 Mg C ha^{-1} depending on the ecosystem (Raich and Schlesinger, 1992; Rees et al., 2005). In agroecosystems, values usually vary between 4 and 15 Mg C ha^{-1} yr^{-1} (Liebig et al., 2005; Rees et al., 2005). The contribution of root respiration is variable, with an average estimation of 24% of the CO_2–C evolved from the soil (Raich and Schlesinger, 1992). In pampean agroecosystems, CO_2–C emissions from microbial respiration ranged from 4 to 12 Mg C ha^{-1} yr^{-1}, falling within expected values.

Management practices impact CO_2–C emissions from the soil. The increase in C inputs due to rotation intensification or the use of crops with high biomass production leads to increases in soil respiration because of greater substrate availability for microorganisms (Amos et al., 2007). The tillage system also impacts soil respiration. Usually, greater seasonal or yearly CO_2–C fluxes are found under tillage than under no-till (Omonde et al., 2007), which has been attributed to higher temperatures in tilled soils (Franzluebers et al., 1998) or to faster decomposition of buried residues (Curtin et al., 2000). Nevertheless, in some cases respiration is similar (Drury et al., 2006) or even greater (Oorts et al., 2007) under no-till, a possible consequence of the accumulation of organic reservoirs in untilled soils (Oorts et al., 2007). The impact of management on the CO_2–C flux has been attributed mainly to the changes produced in the soil temperature and water content (Sainju et al., 2008). The experiments used here for the development of the CO_2–C emissions model were designed for testing tillage effects on soil respi-

Table 4. Inputs of C and soil C balance for two subregions of the Pampas during four 4-yr periods.

Parameter	West Pampa				Rolling Pampa			
	1973–1976	1983–1986	1993–1996	2003–2006	1973–1976	1983–1986	1993–1996	2003–2006
Crops carbon input, Mg ha^{-1}	2.16	2.87	3.65	3.67	1.36	3.94	3.62	3.68
Wild vegetation C input, Mg ha^{-1}	1.87	1.32	0.51	1.58	1.53	0.54	1.36	1.20
Total C input, Mg ha^{-1}	4.03	4.19	4.16	5.25	2.89	4.48	4.98	4.88
Soil C balance, Mg ha^{-1}	–0.95	–0.79	–0.82	0.27	–4.56	–2.97	–2.47	–2.57

ration. Some of them showed significant but small changes in the CO_2–C fluxes induced by tillage but others showed no difference in the CO_2–C emissions between tillage treatments. When microbial respiration was modeled and all data integrated, tillage system had no significant effect on the CO_2–C flux. The possible tillage effect may be subrogated by other variables included in the network model, such as soil temperature and water content.

Previous work has shown that neural networks can make better predictions of crop yield at regional (Alvarez, 2009) and plot scales (Kaul et al., 2005) than regression techniques. Our results show that neural networks can also predict crop C inputs to the soil better than linear models, showing the ability to describe complex relationships between yield and biomass production. Usually, C inputs from crops to the soil have been estimated using fixed coefficients applied to yield data (Bolinder et al., 2007). The simplicity of this approach is counteracted by the problem of a great variability in harvest indices, depending on the environmental conditions. This phenomenon was more important for wheat and soybean in our pampean agroecosystems, in which using the average harvest index would produce biased estimation of C inputs of about 40% in many situations. The harvest index of wheat and soybean were negative and nonlinearly related to rainfall during the growing cycle so, as rainfall increased, C inputs were greater for a given yield. In natural (Del Grosso et al., 2008) and cultivated ecosystems (Álvaro-Fuentes et al., 2008), net primary productivity and C inputs increase with rainfall. This process occurred in our pampean agroecosystems as a consequence of greater yields of all three crops studied and of a lower harvest index in wheat and soybean.

Average belowground C inputs from roots and rhizodeposition have been estimated as 0.3 Mg C for each 1 Mg of straw input, according to 45 experiments performed with corn (Amos and Walters, 2006). Analyzing the results from 23 experiments performed with corn, soybean, and small-grain cereals, the mean belowground C input was equivalent to 20% of the net primary productivity, with an average harvest index of 0.5 for corn and 0.4 for soybean and small-grain cereals (Bolinder et al., 2007). This would lead to an input of 0.4 to 0.5 Mg C belowground for each 1 Mg of straw C input, depending on the crop. Our data fall between these estimations. An average of 0.47 Mg C per 1 Mg of straw input was estimated without differences among crops.

Soil C budget results from different agroecosystems show a wide variation. Usually negative budgets have been estimated, with losses from −0.7 to −7 Mg C ha^{-1} yr^{-1} (Mu et al., 2008, Takata et al., 2008). In some cases, soils C levels were near steady state, with only very small changes of −0.02 to −0.03 Mg C ha^{-1} yr^{-1} (Buyanovsky et al., 1987; Duiker and Lal, 2000), and even, in some agroecosystems, budgets were positive, with C gains from 0.1 to 4 Mg C ha^{-1} yr^{-1} (Matsumoto et al., 2008; Mu et al., 2008). We estimated, in the pampean soils, C budgets ranging from −4.56 to 0.3 Mg C ha^{-1} yr^{-1} during the crop phase of the common rotations used in the region. Our estimations indicate that budgets were negative in the past but C gains may be expected now in some soils as a consequence of the increase in crop C inputs and, as in other agroecosystems (Matsumoto et al., 2008), because of the biomass contributions of weeds and wild vegetation. Overestimation of C losses may be produced in our data because soil C contents used for C budget prediction in typical soils of the West and Rolling Pampas was performed using soil map data. Soil surveys were performed in these areas between 1960 and 1970. Consequently, the actual C contents of the soils may be lower than those used for CO_2–C emissions calculation and C fluxes.

Different approaches have been used for evaluating soil or ecosystem C budgets at the regional scale. The determination of the CO_2–C flux from the soil excluding crop roots has been assessed for empirical modeling by regression methods from heterotrophic respiration, and C inputs estimated by satellite images, allowing soil C budget calculation (Takata et al., 2008). A regression tree methodology was developed that predicted net ecosystem exchange, for which the input variables were soil use, time, and some spectral reflectance indices (Xiao et al., 2008). This regression tree could explain 53% of the net ecosystem exchange from various ecosystems such as croplands, woods, and savannas. The net ecosystem exchange was first determined in field experiments for regression tree model development, and satellite image information was used for extrapolating the results to the country scale in the United States. Simulation models have also been used for net ecosystem exchange estimation by simulating gross primary productivity and ecosystem respiration (Ito, 2008). These modeled CO_2–C emissions data were validated against experimental results and extrapolated to the semi-continental scale in East Asia. Our approach for C budget estimation by neural network modeling of CO_2–C flux and crop C inputs to the soil was developed for estimation mainly at the ecosystem scale. The possibility of applying this methodology at the regional scale depends on further research on the validity of extrapolating the results using average data of soil characteristics, climate, and crop yields. Because the responses of CO_2–C flux and crop C inputs to the soil to independent variables were not linear, and complex interactions existed between them, averaging the data of soil characteristics, climate, and crop yields for heterogeneous areas may introduce serious bias in C budget estimations. Information on biomass production of wild vegetation is also needed for validation of the Century estimations performed in this study.

The Pampas is an area with high net primary productivity and great potential for C sequestration and climate change mitigation (Zomer et al., 2008). Using the normalized difference vegetation index, it has been estimated recently that the region lost around 24 Tg of its net primary productivity during a 23-yr period due to soil degradation (Bai et al., 2008). Our results indicated that these losses were not produced by residue C input reductions from the introduction of soybean in rotations. The substitution of pastures for crops, a general phenomenon in the region (Ministerio de Agricultura, Ganadería y Pesca, 2010), may be the cause of these losses. Using the Century model, increases in the soil organic C content have been estimated between 1980 and 2000 in the soils of the United States (Negra et al., 2008). The network models developed here estimated a positive C budget in some pampean soils under cropping, which would lead to C sequestration, but important losses are still occurring in other soils. The magnitude of this process must be studied at the regional scale. The possibility of prediction of the soil C budget in the future using the fitted network depends on the magnitude of the changes in the harvest index and the shoot/root ratio by genetic improvement. As long as these variables do not change markedly during the next decades, the models developed here would be useful for soil C change forecasting.

CONCLUSIONS

Artificial neural networks were better tools than regression techniques for estimating the soil C balance in pampean agroecosystems because of a more adjusted prediction of soil CO_2–C emission and of crop C inputs to the soil. In these agroecosystems, the soil C balance may be positive or negative depending on the soil C content, environmental conditions, and the rotation used.

A historical analysis of the evolution of the soil C balance showed that the introduction of soybean in rotations has had no negative effects on soil C content because the low C input to the soil of this crop was counteracted by greater yields, biomass production, and C inputs from other components of the rotation, as estimated by the neural network approach. The methodology developed here may be applied in other regions for C budget prediction.

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