Interreg CENTRAL EUROPE

Co-funded by the European Union

Carbon Farming CE

REPORT ON ACTUAL AND POTENTIAL CO_2 SEQUESTRATION

CARBON SEQUESTRATION AND MODELLING FUTURE SCENARIOS

DELIVERABLE D.3.3.1

April 2025

CONTENT

INTRODUCTION AND SCOPE OF THE TASK

In the Carbon Farming CE project, the objective of Deliverable 3.3.1 is to model carbon sequestration considering future scenarios in which CF (carbon farming) techniques are applied.

In general, soil organic carbon (SOC) dynamics vary with soil type, climatic condition and, in agricultural systems, with the agronomic management practices adopted (Luo et al., 2019). SOC dynamics are dependent on C inputs (i.e. crop residues and organic amendments) and outputs (i.e. organic matter decomposition and erosion) (Clivot et al., 2019), and C inputs are the predominant factor influencing the SOC balance (Luo et al, 2019). However, changes in SOC content happen over a time scale of decades, and to detect them we need experiments on the same timescale.

Soil is a very complex system characterized by many abiotic and biotic processes and is influenced by different factors that should all be accounted for when running field experiments. Specifically, considering the processes involved in C sequestration, one of the most important factors determining SOC stocks is the balance between C outputs and the C inputs. All these fluxes are influenced by soil type and climatic conditions of the area. To deal with field-scale complexity we need to relate all the factors involved in SOC cycling with mathematical functions, building a model.

The development of mathematical models able to reproduce SOC dynamics and predict future SOC evolutions needs data to calibrate and validate them that can be produced only by long-term experiments (Clivot et al., 2019). In fact, mathematical models represent a useful tool to extrapolate future trends from the information in this data, a tool with which it is possible to have an overview of SOC sequestration leading to a prediction of the driving factors and test hypotheses (Clivot et al., 2019).

Clearly, the application of mathematical models means that involved processes would be abstracted and represented by equations over time. This implies a choice about what to represent. As previously said, soil biochemical processes are complex and dependent on many biotic and abiotic factors that might be active at different time- and spatial-scales and therefore any modelling approach must approximate some of them. These approximations will be based on various trade-off dependent on the model intended application, and after all a model will still be only as good as the data used to build it. Correctly calibrated models could represent a good compromise between complexity, robustness and practical value to be used as support to help managing SOC in arable systems (Clivot et al., 2019). Moreover, SOC models in agricultural systems permit us to investigate the impact of alternative management scenarios and climate variability on SOC dynamics (Luo et al., 2019).

In this context, it has been decided to use the Introductory Carbon Balance Model (ICBM), which has been defined and implemented by Andrén and Kätterer at the Ecology Department of the SLU, Uppsala University. The selection of the ICBM model is motivated by the possibility of considering different climatic conditions and thus of applying and adapting the model to different pedoclimatic areas. The ICBM model allows to determine if a system is losing or sequestering SOC and moreover, it could be utilized also for future prediction also with different scenarios (Andrén, 1997).

APPROACH FOR MODELLING SOIL CARBON

2.1 The Introductory Carbon Balance Model (ICBM)

The model consists of a mathematical description of C cycle from the inputs to C transformation and stabilization in soil. The ICBM model is based on some basic assumptions (Andrén, 1997) (Figure 1):

i. Two pools, young (Y) and old (O), of soil carbon are considered;
ii. Outflows from the pools follow first-order kinetics (k_1, k_2). This means that the rate of C outflux from the system is not constant over time (zero order) but is instead a function of the remaining C itself which varies over time;
iii. Carbon stabilization process is described by the humification constant (h);
iv. External (mainly climatic, but also edaphic) factors can be condensed into one parameter, r_e, which affects the decomposition rates of Y and O equally;
v. Mean annual carbon input to the soil are described by one parameter (i).

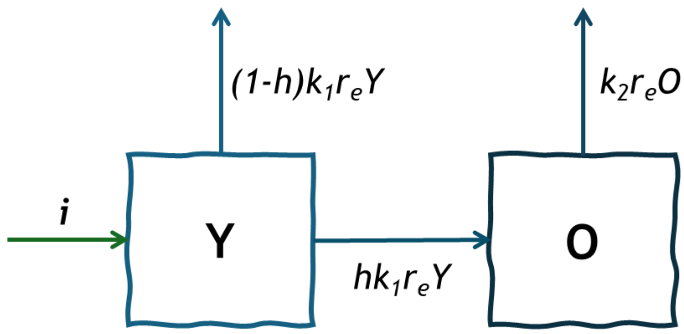

Figure 1 - Representation of pools and fluxes involved in the ICBM model (from Andrén et al., 1997).

In Figure 1 there is a basic scheme of the model with the two pools of C that are connected by the flux of the Y pool that, through the humification process, enters in the O pool. The inputs (i) correspond to the C that annually enters the young carbon pool. The other two fluxes indicate the rate of C losses with the soil respiration process involving Y and O carbon pools.

The model is mathematically composed of a series of differential equations which describe the time variation of Y and O carbon pools (generally express as years), considering all the fluxes reported in the schematic representation of the model. The model could be defined by two main equations (Kätterer & Andrén, 2001):

$$\frac{\partial Y}{\partial t} = i - k_1 r_e Y \qquad (Eq. 1)$$

$$\frac{\partial O}{\partial t} = hk_1 r_e Y - k_2 r_e O \qquad (Eq. 2)$$

The variation of the young C pool (Eq. 1) at time t is defined by the inputs (i) minus the fraction of Y lost at time t-1. The same applies to the old C pool (Eq. 2) but here the inputs correspond to the fraction of C that outflows from Y through the humification process and enters in the O pool.

Once the system is defined in this way, the fluxes from the soil as respiration are given by:

$$\frac{\partial R}{\partial t} = (1 - h)k_1 r_e Y + k_2 r_e O \qquad (Eq. 3)$$

The fraction of C loss by the system with the respiration (Eq. 3) is given by the sum of respired C in the young and old pools at time t. For simplicity, the evolution of carbon dioxide carbon (CO_2-C) was estimated by fitting the difference between the initial amounts of soil C (C_0) and the C present in the Y and O pools at time t (Kätterer and Andrén, 2001).

However, it is necessary to consider that the total amount of C input to Y is determined by plant shoots, roots and root exudates that account for different weight in the total input size and that have different properties, in particular different humification coefficients (Kätterer et al., 2011). Moreover, in agronomic systems, the fraction of C derived from compost, green manure or other amendments must be considered as well. Therefore, shoots (Y_s), roots (Y_r), root exudates (Y_e) and amendments (Y_a) inputs to the Y carbon pool must be mathematically defined as separated pools:

$$\frac{\partial Y_s}{\partial t} = i_s - k_1 r_e Y_s \qquad (Eq. 4)$$

$$\frac{\partial Y_r}{\partial t} = i_r - k_1 r_e Y_r \qquad (Eq. 5)$$

$$\frac{\partial Y_e}{\partial t} = i_e - k_1 r_e Y_e \qquad (Eq. 6)$$

$$\frac{\partial Y_a}{\partial t} = i_a - k_1 r_e Y_a \qquad (Eq. 7)$$

Consequently, Eq. 1 will be modified to account for the sum of the Y input considered:

$$\frac{\partial Y}{\partial t} = (i_s + i_r + i_e + i_a) - k_1 r_e (Y_s + Y_r + Y_e + Y_a) \qquad (Eq. 8)$$

Usually, the fractions of shoots, roots and root exudates input are calculated with allometric equations from above-ground plant production (Kätterer & Andrén, 2001).

2.2 Input estimation and parameters definition

Once the model structure is defined, still inputs and the model parameters (the kinetics constants and the humification coefficients) should be defined.

Starting from the total plant harvested dry matter it is possible to calculate the fraction corresponding to the shoots and roots using the shoot-to-root ratio (S:R) values. Clearly, each plant species is characterized by a different S:R. In this study it has been decided to apply the S:R used in the works of Lazzerini et al. (2014) and Migliorini et al. (2014) as they took in consideration a long-term experimental site in Tuscany, not so far from Bologna sites. Those S:R do not consider the type of management adopted and differentiate crop by S:R values (Table 1) derived from 168 crop data from Canadian agroecosystem studies (Bolinder et al., 2007).

Table 1 - Shoot to root ratio mean values and SD error for different crops (from Bolinder et al., 2007).

Crop		Shoot/root ratio
Small-grain cereals	All studies	7.4 ± 3.6
Winter wheat	Eastern Canada	6.0 ± 1.2
	U.S.	1.1 ± 0.1
Barley	Easter Canada	2.0 ± 0.3
	Western Canada	10.7 ± 3.1
Grain-sorghum	U.S.	11.6
Corn	All studies	5.6 ± 2.8
	Easter Canada	9.5 ± 1.4
Soybeans	All studies	5.2 ± 3.1
Grass species	All studies	1.6 ± 1.2
Legume species	All studies	2.2 ± 0.9

The root exudates fraction has been assumed to be 65% of the root biomass (Bolinder at al., 2007).

For what concerns the kinetic constants values, k_1 and k_2, they could be calculated from litter-bag data (Andrén, 1997) or appropriate values could be found in literature. In this study no litter-bag data was available, k_1 and k_2 values were considered equal to 0.8 and 0.00605 respectively, according with Andrén (1997).

The humification coefficient (h) describes the fraction of crop residues converted in stabilized soil organic matter (Kätterer et al., 2011). This coefficient depends on the type and quality of the material involved in the humification process. The h values could not be available and so their estimation have to be done indirectly, based on long-term experiment data and modelling assumptions. To minimize the dependency on the assumptions and offer a more robust *h* estimate, Kätterer et al. (2011) determined several *h* values for various assumptions reporting a range of *h* values for shoot, root and organic fertilizers. In this study, it has been decided to use the *h* mean value of all the different scenarios proposed by Kätterer et al. (2011), assuming that the amendments have a humification coefficient (h_a) of 0.20, shoots have humification coefficient (h_s) of 0.15 and roots humification coefficient (h_r) has a value of 0.27. It remains to define the humification coefficient of the exudates, which is still a debated issue. Root exudates are composed by organic substrates with low-molecular weight and high bioavailability (Pausch et al., 2016) and, generally, carbohydrates are the most abundant component in the form of mono- and poli-saccharides (Gunina & Kuzyakov, 2015). Therefore, it could be argued that root exudates have a mean residence time more similar to that of shoot material than of root, and consequently its humification coefficient has to be nearest to the shoot humification coefficient. For those reasons in this study a value of 0.20 has been assumed as exudates humification coefficient (h_e).

However, it is necessary to underline that the values attributed to the parameters, at first, will represent only the prior probability distributions defined by average values to which an error will be associated. These parameters will then be combined with the information contained in the data to identify the values distribution that best represent the kinetics and the humification within the model considered.

2.3 Considering climatic interactions

The ICBM model has been developed and calibrated originally on Swedish soil and climate condition and therefore it needs to be updated with a climatic factor when the area of study change (Andrén et al., 2004).

The data needed for climatic calibration are daily mean air temperature, precipitation, solar radiation, wind speed and humidity; if there are data missing (e.g. humidity data are on monthly instead of daily base) it is possible to apply an interpolation function to fill the gaps. Moreover, data concerning soil bulk density and texture composition are needed for estimating the soil hydraulic parameters and calculating the soil water balance.

These data would be used for determining climatic condition effects on soil decomposition processes. First, the soil hydraulic parameters have to be calculated from soil sand, clay and SOC content (Kätterer et al., 2006). Soil evapotranspiration has been then calculated with a function that depend on weather data, such as air humidity, wind speed, air temperature and solar radiation (Kätterer et al, 2006).

Soil water balance is calculated daily and depends on topsoil thickness, evapotranspiration, precipitation, soil wilting point and field capacity. The relative water content (θ_r) is given by the volumetric water content (θ), the minimum water content ($\alpha\theta_{wilt}$) and the water content at field capacity (θ_{fc}) (Andrén et al., 2004):

$$\theta_r = \frac{(\theta - \alpha\theta_{wilt})}{(\theta_{fc} - \alpha\theta_{wilt})} \qquad (Eq. 9)$$

where α is the minimum water store which is a fraction of that at wilting point.

The dependence of the decomposition process on soil water content is given by:

$$r_w = \theta_r^{\gamma} \qquad (Eq. 10)$$

where γ = 1.3, a constant chosen to approximate the water response function.

Soil temperature has been calculated as function of topsoil thickness (mm), mean air temperature and crops cover (Kätterer et al, 2006). The effect of soil temperature on the decomposition rates is (Andrén et al., 2004):

$$r_T = \frac{(T_{soil} - T_{min})^2}{(30 - T_{min})^2} \qquad (Eq. 11)$$

where T_{min} is the lower temperature limit for decomposer activity (here set to -3.8°C).

In the model, the annual climatic condition effects on decomposition are summarized in the r_e factor (see Eq. 1-8), which is given by:

$$r_e = (r_w * r_T) \qquad (Eq. 12)$$

The r_e factor has to be determined for each day and then the annual mean value is utilized in the model.

2.4. Model Calibration

The model has been calibrated within a Bayesian statistical framework (Menichetti et al., 2016). The central idea on which this approach is based is to represent the prior probability distribution of model parameters and data with large numbers of parameter sets, and to calculate the posterior probability distributions of the results (once the new information from the data is added by comparing simulation results with measurements) bringing forward all the parameter sets. This creates discrete distributions, where each element of the population is represented by one parameter set. Due to the large number of sets, the model approximates a continuous probability distribution. The parameters and data uncertainty are defined with distributions expressing the error of each term (in some cases measured, in some cases estimated). By sampling the multidimensional space (where each uncertain term is one dimension defining the space), the approach combines all sources of uncertainty. This approach can be used to update our previous knowledge (represented by the prior probability distributions of the parameters before considering also the new measured data) with new knowledge (deriving from the probability distributions of the measured data), given a certain model structure (e.g. the set of equations that make up the model).

For the optimization of the model it has been used the sampling algorithm in JAGS, which is a standard Metropolis-Hastings, based on a Gaussian shaped likelihood function (Plummer, 2003). Every calibration has been run in two independent Markov chains, each of which was calibrated with 10000 search runs. At the end the chains showed reasonable convergence.

Priors for *k* (kinetic constants) and *h* (humification coefficients) have been considered as normally distributed, with mean values correspondent to those reported in paragraph 2.2. An error has been associated with those mean values (Table 2). The errors relative to the humification coefficients were calculated as the standard deviation of the *h* values for the different scenarios reported in Kätterer et al. (2011), which are the same data used for the calculation of the *h* mean values. For the error of the humification coefficient of root exudates (h_e) it was used the higher error reported for the other *h* values to consider a possible high variation for this parameter which error is unknown.

Table 2 - Priors for the parameters considered in the model and their relative error.

Parameter	Mean value	Error value
k_1	0.8	0.5
k_2	0.00605	0.62
h_s	0.15	0.013
h_r	0.27	0.097
h_a	0.20	0.08
h_e	0.20	0.097

The error associated with the k_1 kinetic constant has been defined arbitrarily but in a precautionary way as it is more than half of the constant value. Parameter k_2 refers to the decomposition kinetics and the turnover of the old carbon pool (i.e. O pool). For the estimation of its associated error, the standard deviation of the reciprocal of the mean residence time has been used for the stable C pool estimated by Barré et al. (2010). Specifically, in the work by Barré et al. (2010) some long-term bare fallow experiments have been considered for the determination of decay of more stable fractions of soil C. Long-term bare fallow experiments are characterized by the absence of C input with the aim to consider only stable C pool in the soil. In this way it is possible to estimate empirically the more stable C decay by assuming first order kinetics (Barré et al., 2010). In their study, Barré et al. (2010) used a mathematical model composed of two pools, one decaying according to first order kinetics and one inert representing a small fraction of total remaining SOC. The kinetic of the single decaying pool in absence of inputs becomes quite similar to the old pool in ICBM, and so it could be argued that the kinetics of the two models were roughly comparable. The kinetic constant k_2 could be assumed as the reciprocal of the intermediate turnover time calculated by Barré et al. (2010). In this way the standard deviation of the intermediate turnover time reciprocal values could be used as error for the k_2 value.

Finally, the model initial state was described by a term expressing the proportion between the old and all the young pools. The prior for this term has been assumed as uniform and varying between 95% and 100%, quite similar to those used for the Swedish experiments model (Menichetti, personal communication). In this way, a precautionary approach has been used without defining a fixed value for the initialization.

For each run of the model, the calibration considers one different value for every parameter considered, thus exploring all the possible values that each parameter could assume within this set of data and in consideration of the priors previously defined. The final output of the calibration, the posterior probability distributions, represent the values of the parameters identified by the calibration as the most probable for the model within the set of data used.

In Figure 2, the density distribution of the probability for both priors (in grey) and posteriors (colored) values relative to all the parameters considered in the model are reported. The density distribution of both priors and posteriors resulted from the unification of all the Gaussian distribution calculated for each parameter value and is determined by kernel density estimation.

Since we had only one single data point per year, the error in the data has been estimated as the root mean squared error of a linear regression.

Observing Figure 2A, it must be highlighted that for the h_s, h_e, and h_r parameters, the posteriors have a higher uncertainty compared with the priors. This could be due to the high variance and low contrasts in the dataset considered. Instead, considering the distribution of the h_a posteriors, it is possible to deduce that the calibration found more suitable values to describe these data.

Similarly, in Figure 2B, for the h_s, and h_a parameters the posteriors have a higher uncertainty compared with the priors and this could be due to the high variance (h_s) and absence of data (h_a) in the dataset considered. Instead, considering the distribution of the h_r and h_e posteriors it is possible to deduce that the calibration found more suitable values to describe these data, lower than the priors.

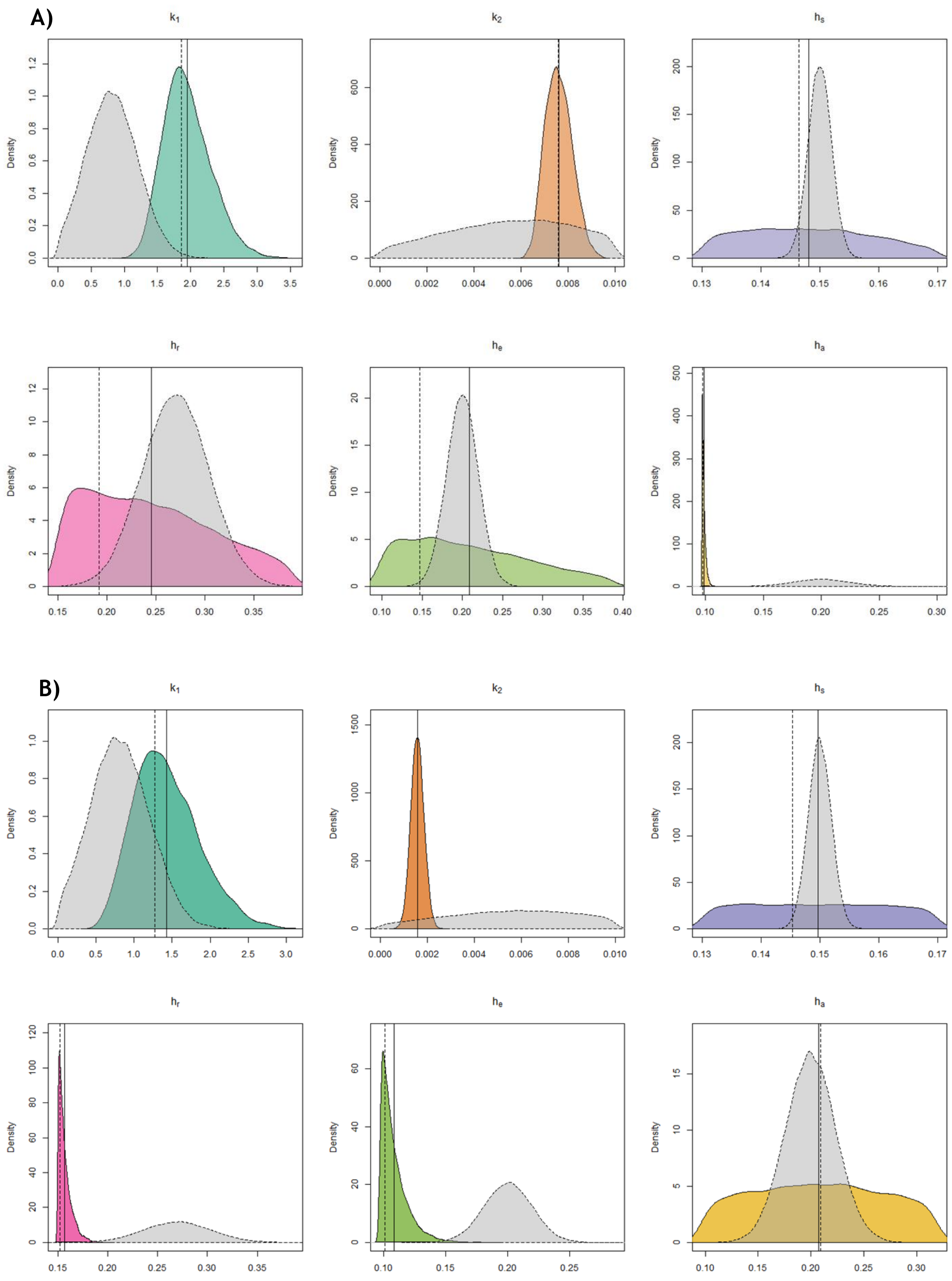

Figure 2 - Graphical representation of the probability density distribution of the priors (in grey) and the posteriors (colored) relative to the parameters considered in the model for A) Trial 29 and B) Trial 64. Solid lines represent mean of the posteriors distribution while dashed line represent the mode of the posteriors distribution.

MODEL RESULTS

The model was implemented in two long-term experimental trials at UNIBO, in which two CF techniques were evaluated.

Two long-term field trials have been selected, where two of the CF techniques identified in D 1.1.1 are being tested. Both trials are located at the experimental farm of the University of Bologna in Cadriano (about 10 km from Bologna), in the south-east of the Po Valley (Italy, 44°33' N, 11° 24' E; 23 m a.s.l.).

The two trials selected (Trial 29 and Trial 64) correspond to the CF techniques identified in the D 1.1.1 as:

A.1 – External organic fertilizer

> TRIAL 29: wheat-corn rotation characterized by the supply of manure, crop residues, and no organic supply (Control), with mineral N addition (at a dose of 200 kgN ha-1 yr-1) or without mineral N addition

B.2 – Crop rotation

> TRIAL 64: the crop rotation involved in the trial are: continuous wheat, continuous corn, biennial rotation corn-wheat, two 9-year rotation both including: corn-wheat-corn-alfalfa-alfalfa-alfalfa-wheat-corn-wheat (the two 9-year rotation differ for the "starting" crop, thus resulting staggered over time).

In this context, the objective was to assess the efficacy of the model in describing the capacity of the implemented CF techniques to promote C sequestration over time. Additionally, the potential of the ICBM mathematical model as a predictive approach to the potential future sequestration of C in soil as a result of changes in agronomic techniques was tested, enabling the prediction of potential future scenarios.

The model was constructed and analysed within the context of northern European environments, and its application in southern European environments can serve as a validation of the model in trans-national settings.

3.1 Trial 29

The data related to Trial 29 referred to the period 1972-2011 which corresponds with the period of experimentation with the higher number of data collected. Data related to crop rotation, crops harvested dry matter and SOC content have been kindly supplied by professor G. Baldoni and Dott. L. Negri (Department of Agricultural and Food Sciences, University of Bologna) and their research group. Instead, climatic data have been supplied by professor S. Ventura (Department of Agricultural and Food Sciences, University of Bologna).

Summarizing, in the experimental site there is a biennial crop rotation involving wheat and corn with a comparison between three fertilization strategies: no treated control, crop residues supply, and manure supply (25 and 30 t ha-1 yr-1 every other year). Details on the experimentation are reported in Deliverable 3.2.1.

The overall carbon inputs between 1972 and 2011 are reported in Figure 3 and they were approximately the same for manure and crop residues CF techniques (363 and 350 t ha-1, respectively). The two systems, however, differ for the source of carbon entering in the soil, indeed the manure once had got a significant fraction of C from the amendments and the crop residues once present a higher fraction of C deriving from shoots. Instead, control showed the lower values with C only deriving from roots and exudates. Therefore, considering that SOC sequestration processes are input driven, it is expected to observe significant differences between the CF techniques in the model results.

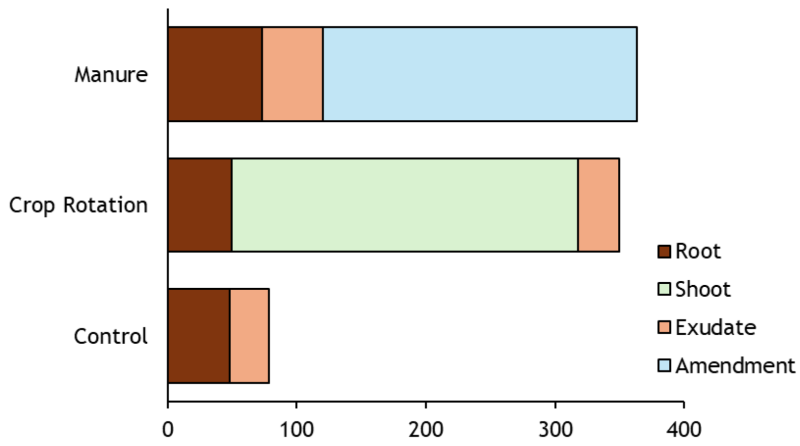

Figure 3 - Total carbon input from 1972 until 2011 expressed as ton per hectare.

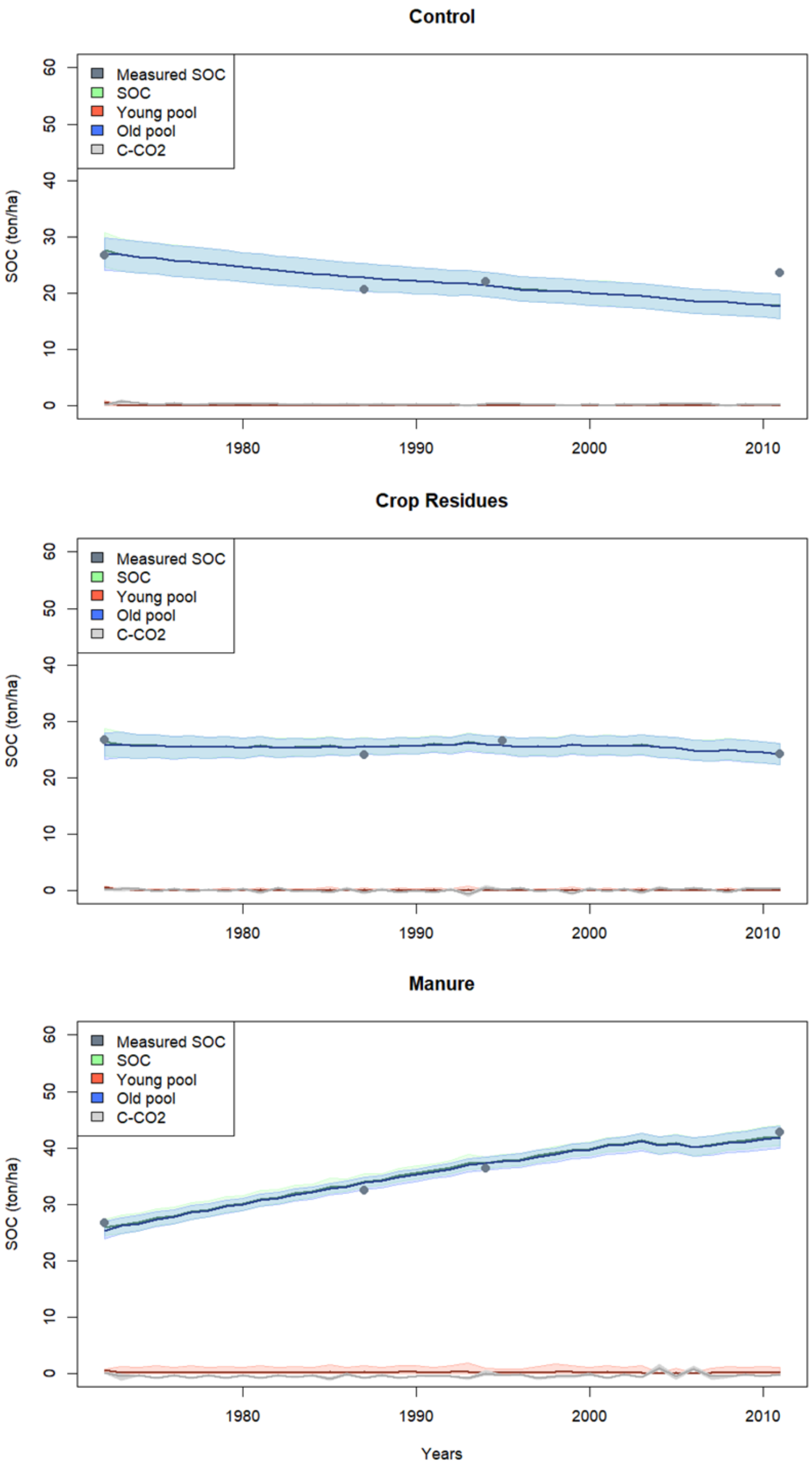

Figure 4- Simulation of SOC pools (young fraction of C in red, Old and stabilized fraction of C in blue, the sum of young and Old is represented by the SOC in green, and the CO_2 loss by the system is in light grey) as described by model structure together with the measured data (grey dots), for the fertilization treatments characterizing Trial 29

Model simulations for those 39 years of experimentation are reported in Figure 4. For all the systems the carbon pools considered (young and old), the total SOC, and the CO2 loss from soil are represented. The lines indicate the model that corresponds to the means of the distribution of all possible models, and in some extent, it could be considered as the model with the higher probability to fit with parameters distribution and measured data. The light shaded colored areas represent all the other possible models that depend on the error associated with the parameters and on measured data.

It is possible to observe that model simulation for all the carbon pools considered has a low uncertainty (thin shaded colored areas), which means that the calibration has found not many acceptable solutions given the priors for those pools. Moreover, model simulation perfectly fits with measured data.

In general, the model highlights that only the control is losing carbon due to the significant lower inputs that arrived in the soil. Manure increased the carbon sequestered into the soil, while crop rotations seem to maintain the SOC content unchanged over the years.

Comparing SOC modeled data for the three systems (Figure 5) it is possible to observe that SOC increase in the three systems has been significantly different, indeed it has been calculated a yearly mean variation of -0.11, +0.13 and of +2.63 (ton ha-1 yr-1) for control, crop residues and manure respectively. This clearly expresses the dependency of the model from the measured C input. Indeed, upon consideration of the C inputs measured over a 39-year period (363 and 350 t ha with manure and crop residue, respectively) and consideration of the C increases observed in soils, it was determined that the C from manure was stabilized at a rate of 28% of the input, while the C from crop residue was stabilized at a rate of 1.4%. Consequently, the quality of the residue has a substantial impact on its capacity to stabilize in the soil.

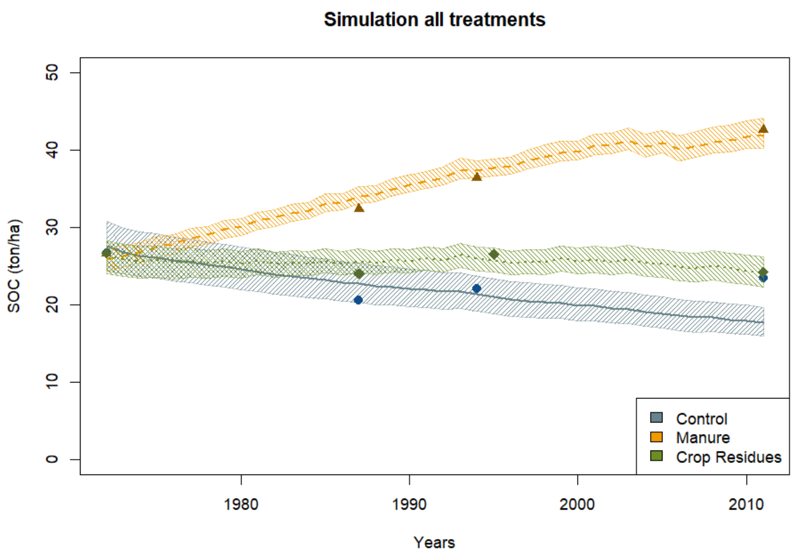

Figure 5 - Simulation of SOC content together with measured data for control (grey), manure (orange) and crop residues (green) fertilization treatments.

3.1.1 Future projection in Trial 29

The ICBM model, like all the mathematical models, can estimate future SOC sequestration thus giving the opportunity to test hypotheses on how different management strategy could impact carbon stock.

Within Trial 29, two different scenarios have been hypothesized with different fertilization strategies (i.e., different CF techniques) until the year 2044. The choice of a long period of time has been done with the aim to get close to the steady state condition for soil C sequestration, when SOC stocks will reach a dynamic equilibrium, and their variation will become zero. This state represents the maximum SOC sequestration potential attainable of a certain system and is mathematically defined by the first order theory of SOC decay.

In the first scenario, after 39 years in control trial (i.e., no fertilization and no crop residues incorporation) has been supposed the introduction of manure supply (25 and 30 t ha-1 yr-1 every other year) for the other 33 years; in the second scenario, followed to crop residues it has been supposed the introduction, in addition to crop residues incorporation, of manure supplied at a rate of 25 t ha-1 yr-1 every other year (Figure 6).

Model results (Figure 6) highlight that the first scenario will have higher capacity to sequester soil organic C than the second one. Indeed, the increase of SOC will be approximatively of 40 t ha-1 in the first scenario and of 25 t ha-1 in the second scenario (from 2011 to 2044). This result could be ascribed to the different amount of carbon input, that will be higher in the first scenario but also to a different C sequestration rate capacity.

Comparing the two projections for the future scenarios hypothesized (Figure 7) it appears that carbon sequestration rate with the first scenario would be in general higher, while the second one start to reduce its C sequestration rate capacity earlier.

Model results for the future projections also showed higher uncertainty (thick shaded colored areas), which means that the calibration has found many acceptable solutions given the priors for those pools. Anyway, also considering the worst prediction (orange dotted lines in Figure 7) it is possible to observe an increase in C sequestration from 2011 to 2044 with both the scenarios proposed.

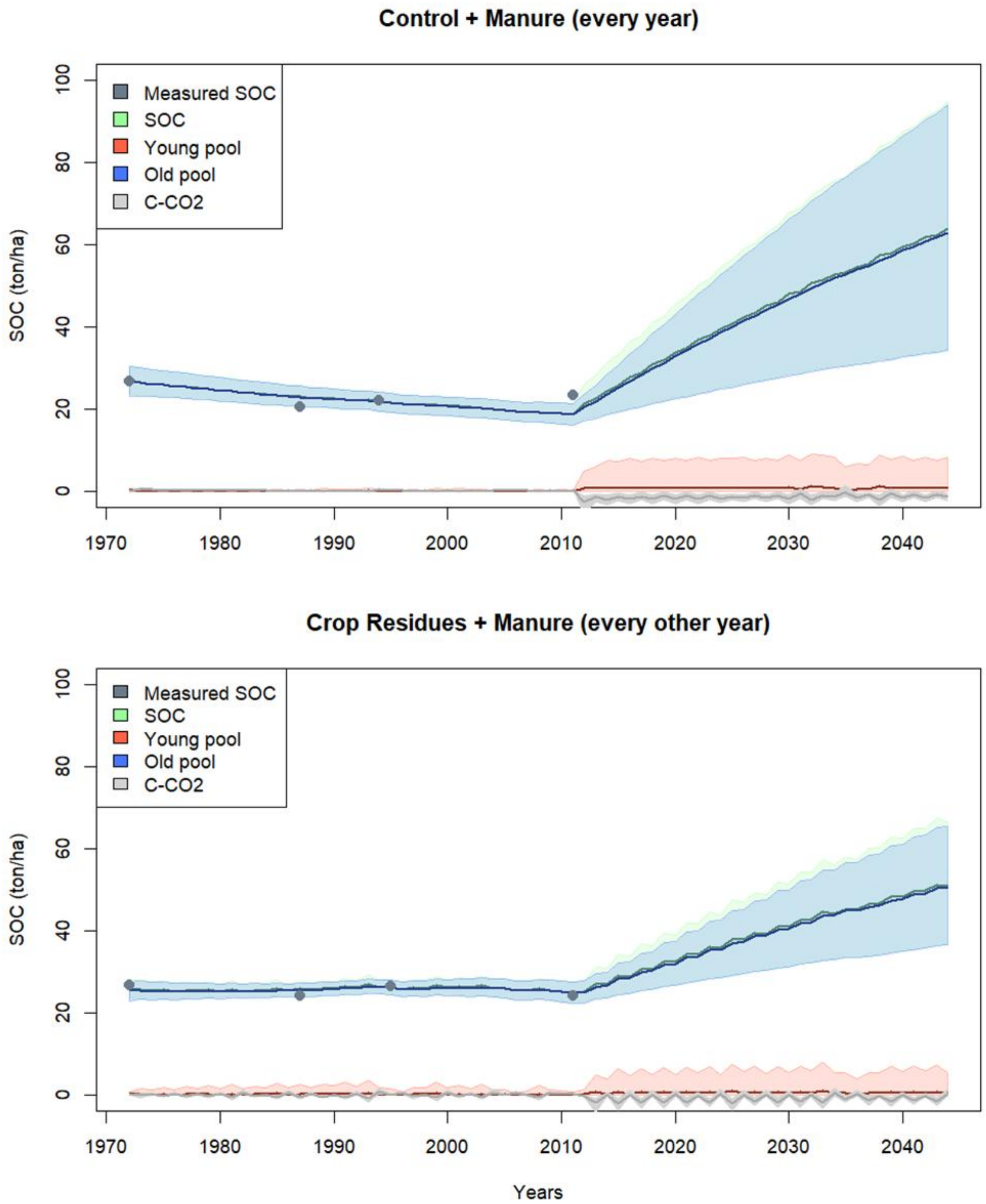

Figure 6 - Simulation of SOC pools (young fraction of C in red, Old and stabilized fraction of C in blue, the sum of young and Old is represented by the SOC in green, and the CO2 loss by the system is in light grey) as described by model together with the measured data (from 1972 to 2011, grey dots) for control + Manure and for Crop residues + Manure.

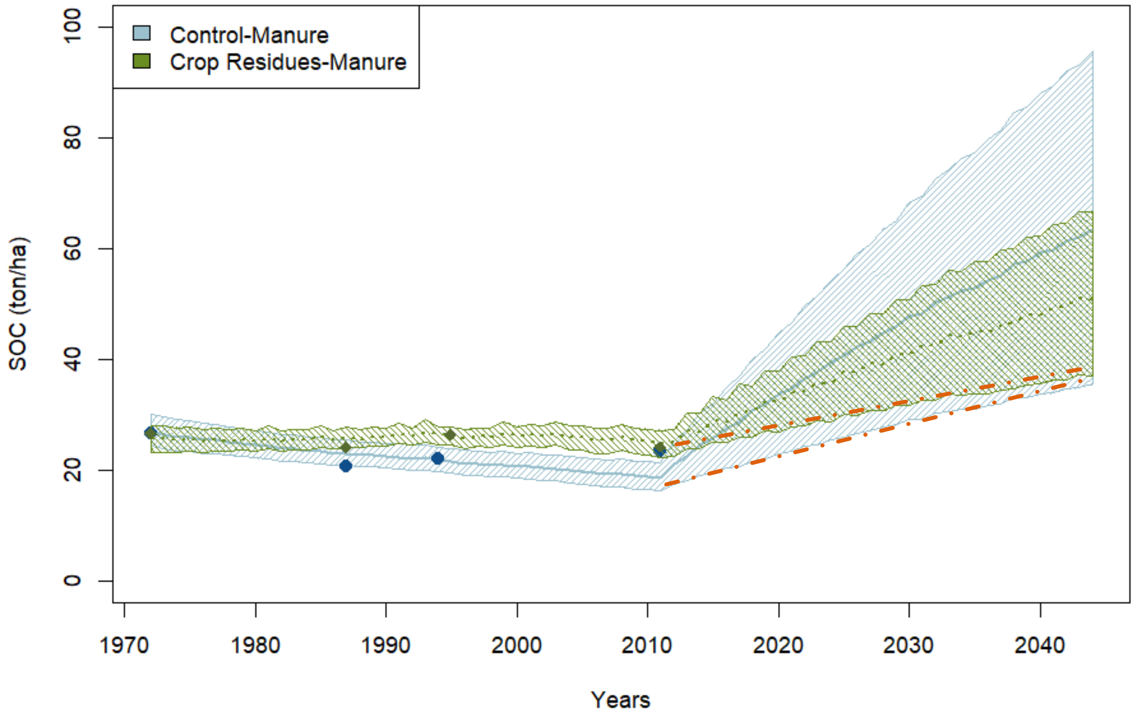

Figure 7 - Comparison of the simulation of SOC content for the two scenarios hypothesized in Trial 29.

3.2 Trial 64

The data related to Trial 64 referred to the period 1972-2011 which corresponds with the period of experimentation with the higher number of data collected. Data related to crop rotation, crops harvested dry matter and SOC content have been kindly supplied by professor G. Baldoni and Dott. L. Negri (Department of Agricultural and Food Sciences, University of Bologna) and their research group. Climatic data have been the same used for Trial 29 as the two experimental sites are close to each other.

Summarizing, in this experimental site there is a comparison between 4 crop rotation strategies with no external fertilizers: continuous corn, continuous wheat, biennial rotation corn-wheat, nine-year rotation with corn-wheat-alfalfa (distributed over several plots because it was made to start from different crops in the rotation, i.e. at the beginning of the trial corn was sown in rotation 9-yr (1), and alfalfa in 9-yr (2)). Details on the experimentation are reported in Deliverable 3.2.1.

The overall carbon inputs between 1972 and 2011 are reported in Figure 8 and they were approximately the same for continuous corn and biennial rotation corn-wheat (15 and 16 t ha-1, respectively). Continuous wheat supplied the lowest amount of C (7 t ha-1 in 39 years), while the two nine-year rotations apported the higher C input to the soil (94 and 71 t ha-1 for 9-yr (1) and 9-yr (2), respectively). The rotations do not differ for the source of carbon entering in the soil; indeed, no crop residues or amendments have been supplied and thus C only derived from roots and exudates. Therefore, considering that SOC sequestration processes are input driven, it is expected to observe only slight differences between the crop rotation in the model results.

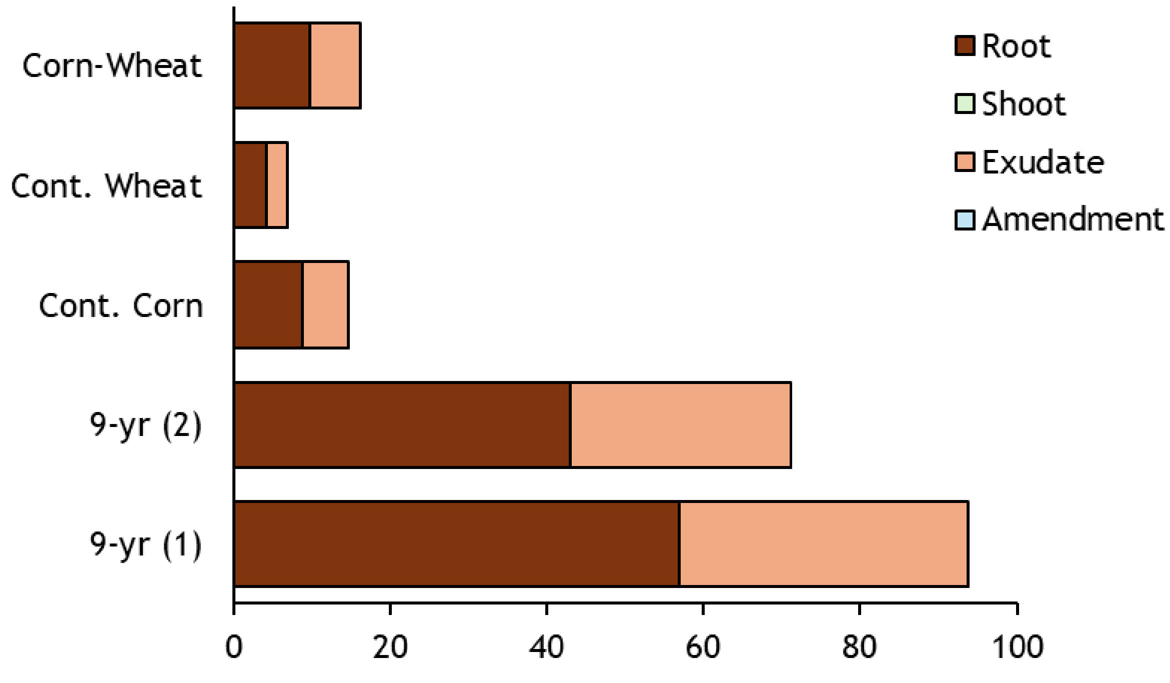

Figure 8 - Total carbon input from 1972 until 2011 expressed as ton per hectare.

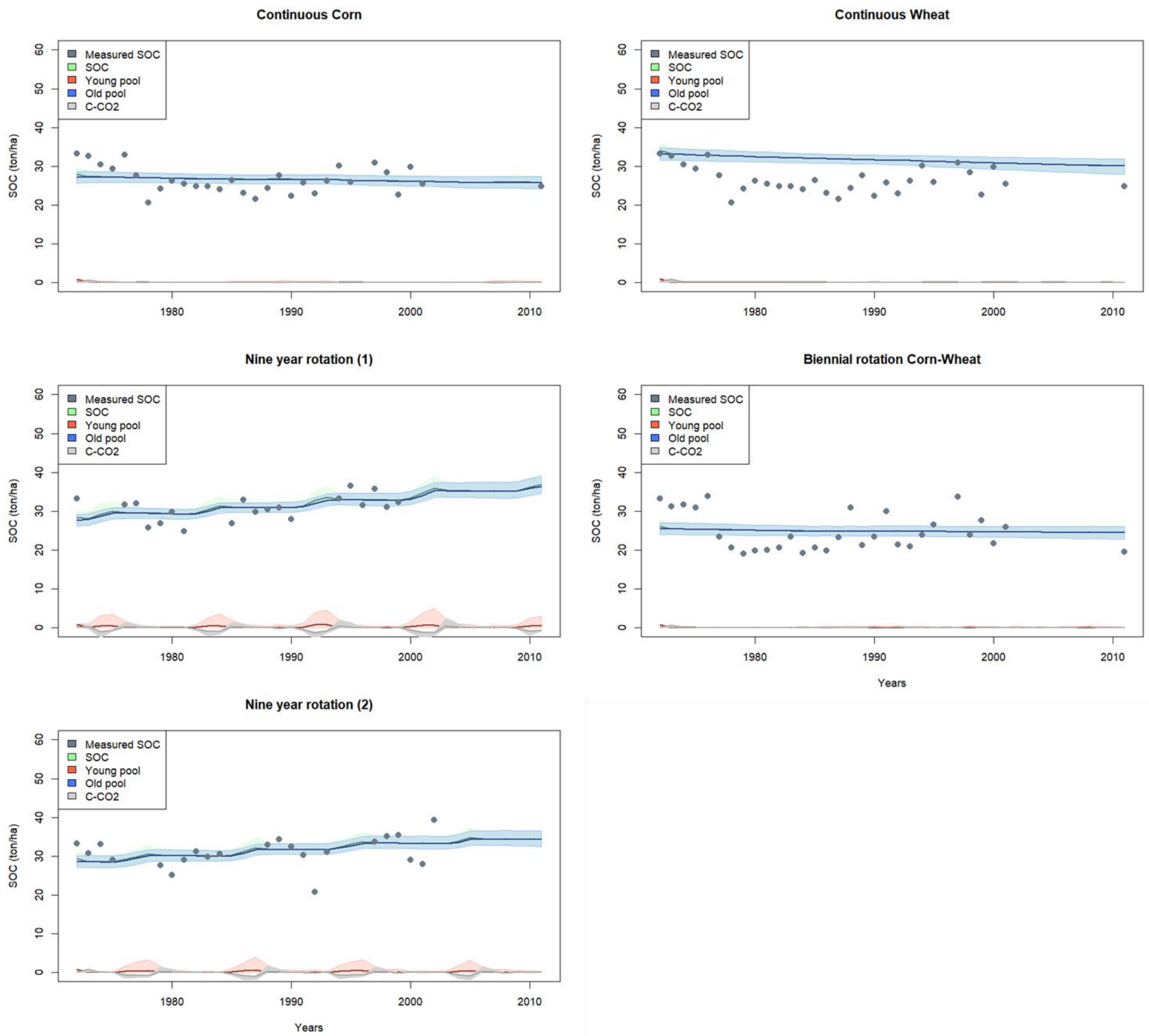

Figure 9 - Simulation of SOC pools (young fraction of C in red, Old and stabilized fraction of C in blue, the sum of young and Old is represented by the SOC in green, and the CO_2 loss by the system is in light grey) as described by model structure together with the measured data (grey dots), for the crop rotations characterizing Trial 64.

Model simulations for those 39 years of experimentation are reported in Figure 9. For all the systems the carbon pools considered (young and old), the total SOC, and the CO2 loss from the soil are represented. The lines indicate the model that corresponds to the means of the distribution of all possible models, and in some extent, it could be considered as the model with the higher probability to fit with parameters distribution and measured data. The light shaded colored areas represent all the other possible models that depend on the error associated with the parameters and on measured data.

It is possible to observe that model simulation for all the carbon pools considered has a low uncertainty (thin shaded colored areas), which means that the calibration has found not many acceptable solutions given the priors for those pools. For this experimental site a higher number of SOC measurements were available and thus for sure the model has been calibrated with high precision.

The model highlights that only continuous wheat is losing carbon due to the significant lower inputs that arrived in the soil. Continuous corn and biennial rotation showed a constant trend over time. The two nine-year rotations are the only that increased the carbon sequestered into the soil, with an overall increase that is from 10 to 15 t ha-1 in 39 years.

Comparing SOC modeled data for all the crop rotations (Figure 10) it is possible to observe that from the SOC starting point defined by the model the increase in the five systems has been significantly different, indeed it has been calculated a yearly mean variation of -0.12, +0.23, +0.26, +1.64 and +2.03 (t ha-1 yr-1) for continuous wheat, continuous corn, biennial rotation, nine-year (2) and nine-year (1) respectively. Indeed, upon consideration of the C inputs measured over a 39-year period and of the C increases observed in soils, it was determined that even if C input were to be minimal, the percentage of C stabilization would still be significant in continuous corn, biennial rotation, and nine-year rotation (which have a positive mean variation of C in the soil). In continuous corn, biennial rotation, and the two 9-year rotations (1 and 2), C was stabilized at rates of 60%, 63%, 84%, and 91%, respectively. The findings demonstrate that the quantity and quality of the residues that were deposited in the soil are directly proportional to the rate of C stabilization. This relationship is further substantiated by the indirect effect of the prolonged absence of soil tillage in the 9-year rotations when alfalfa is present.

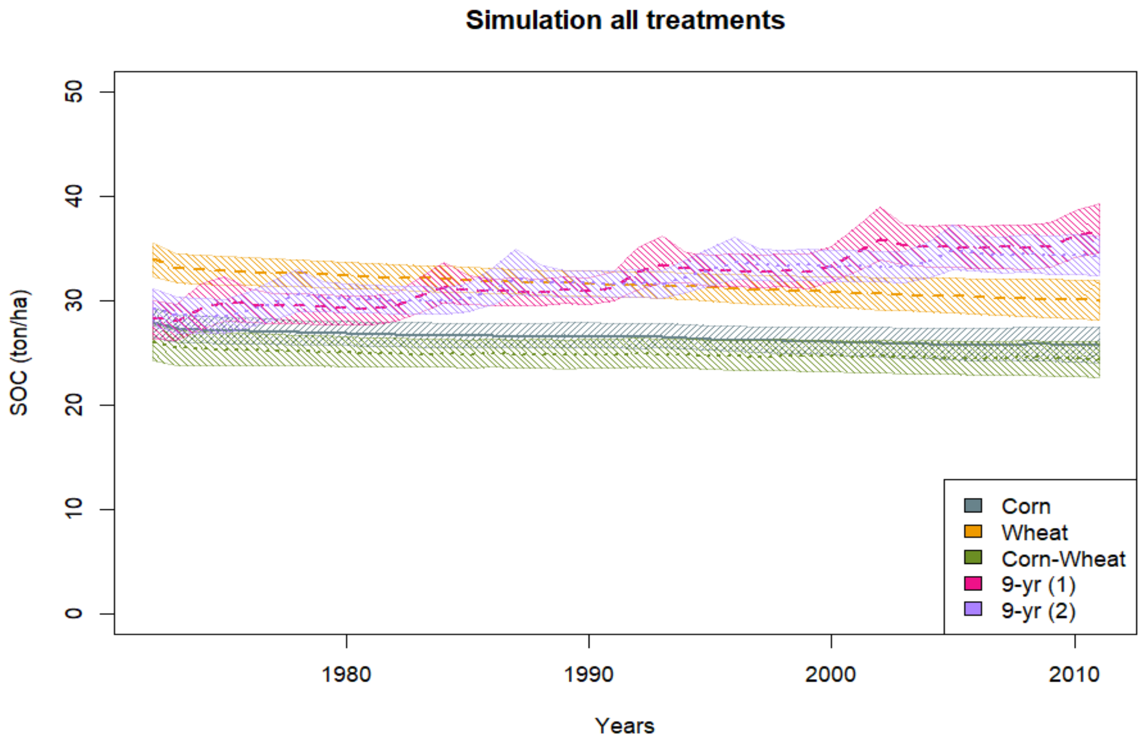

Figure 10 - Simulation of SOC content for continuous corn (grey-blue), continuous wheat (orange), biennial rotation corn-wheat (green), 9-year rotation 1 (pink) and 9-year rotation 2 (violet).

3.2.1 Future projection in trial 64

Within Trial 64, different scenarios have been hypothesized with different fertilization strategies (i.e., different CF techniques) until the year 2044.

In the first scenario (Figure 11), after 39 years has been supposed the introduction of manure supply (20 t ha^{-1} yr^{-1} every other year) for 26 years and the crop residues incorporation for the last 7 years considered in the scenario; in the second scenario (Figure 12), followed to continuous corn and continuous wheat has been supposed the introduction of alfalfa in with the same approach used in the 9-year rotations.

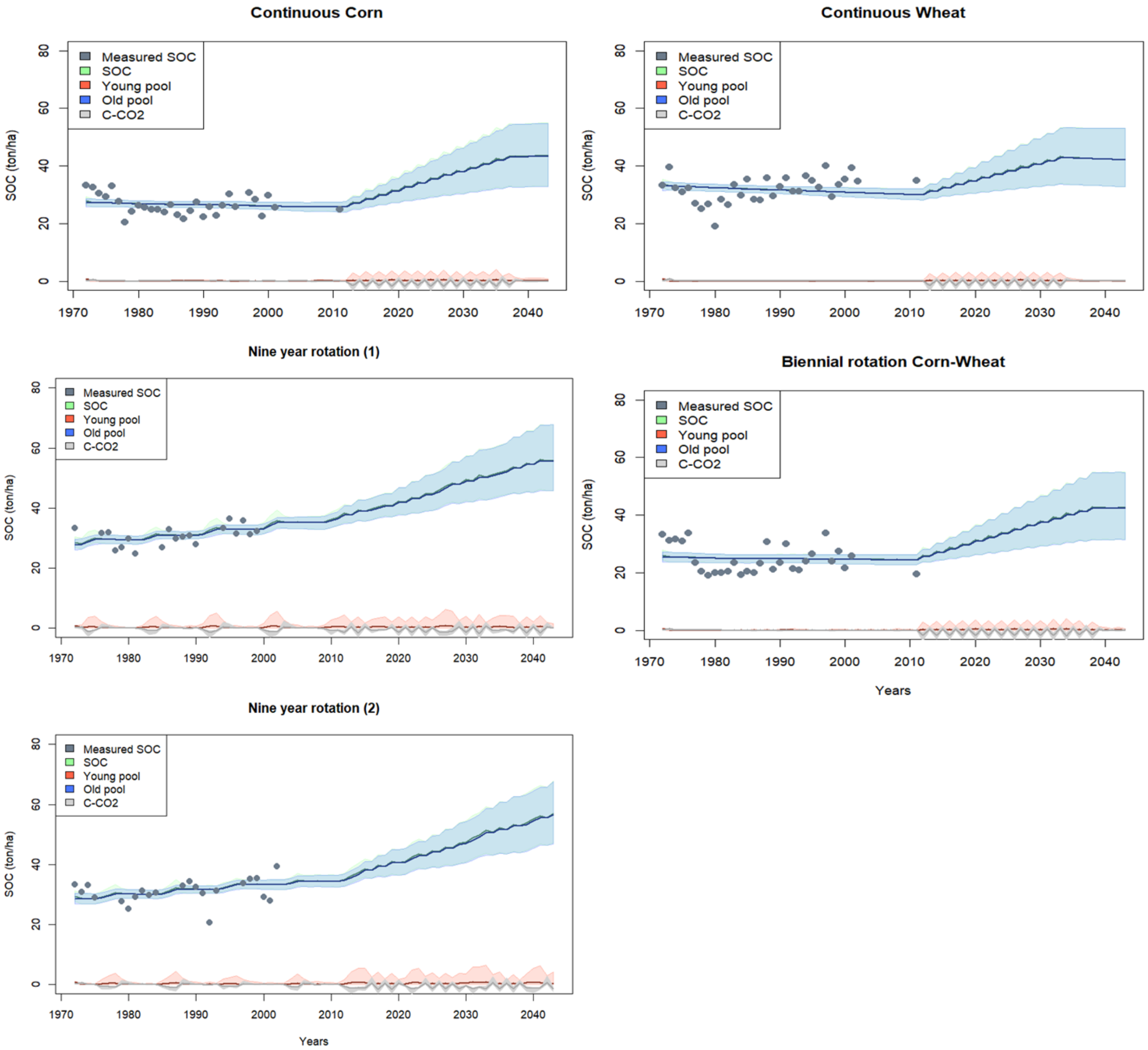

Figure 11 - Simulation of SOC pools (young fraction of C in red, Old and stabilized fraction of C in blue, the sum of young and Old is represented by the SOC in green, and the CO_2 loss by the system is in light grey) as described by model together with the measured data (from 1972 to 2011, grey dots) assuming manure supply every other year for all the crop rotation considered.

Model results for the first scenario (Figure 11) highlight that manure supply will have high capacity to favour soil organic C sequestration. In particular, the growth curve of sequestered SOC is steeper in plots characterized by continuous corn and wheat rotations and biennial rotation. In plots with the nine-year rotation, potential C sequestration is greater than in other rotations, but the increase seems to be less abrupt. Moreover, with the two nine-year rotation the shaded colored areas indicating all the possible models are thinner than those of the other rotations thus indicating that the inclusion of manure in this rotation just improves the trend that anyway the system already has. On the contrary, with continuous corn, continuous wheat and biennial rotation with the introduction of manure we observe a net change of trend in terms of C sequestration; indeed, the initial point is characterized by lower organic C levels, resulting in a pronounced gear shift.

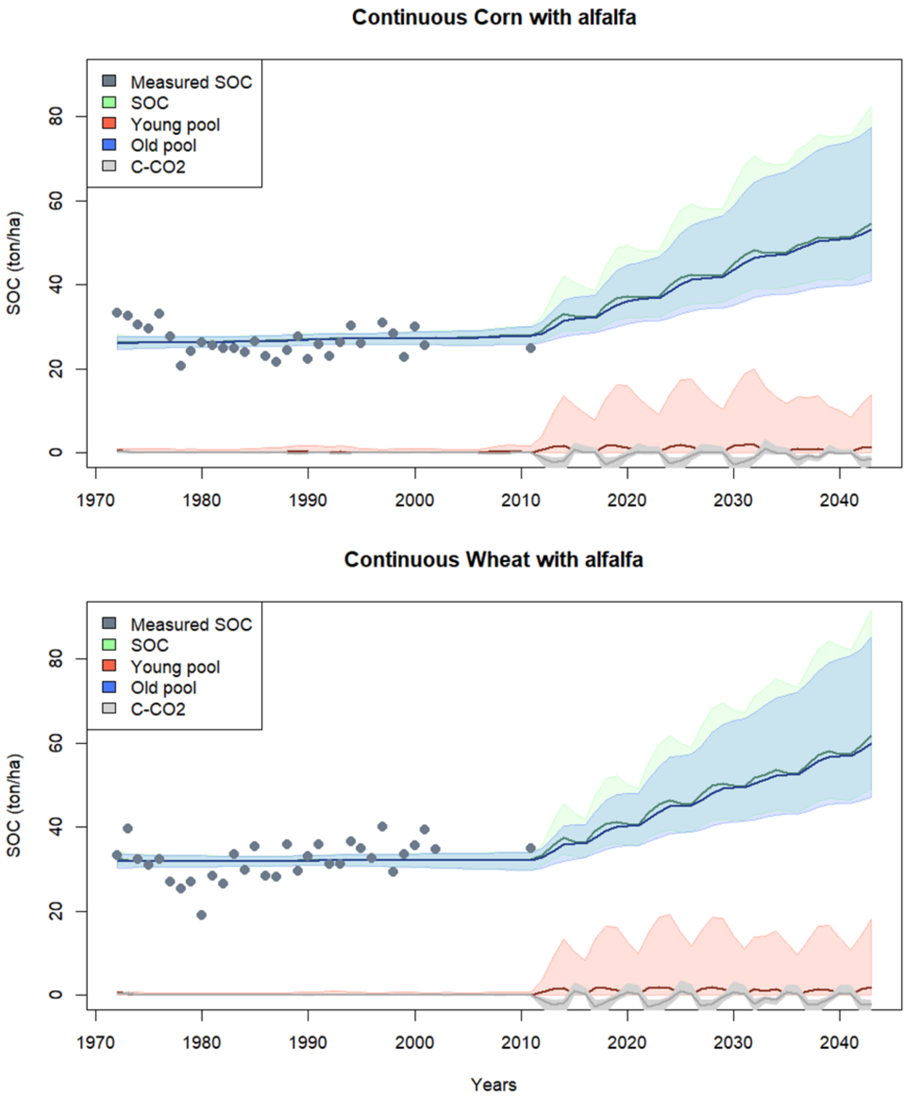

Figure 12 - Simulation of SOC pools (young fraction of C in red, Old and stabilized fraction of C in blue, the sum of young and Old is represented by the SOC in green, and the CO2 loss by the system is in light grey) as described by model together with the measured data (from 1972 to 2011, grey dots) assuming the inclusion of alfalfa in the crop rotation (continuous corn and continuous wheat).

Results for the second scenario (Figure 12) showed that also the inclusion of alfalfa in the crop rotation could be a good strategy to increase carbon sequestration: the rate of increase of SOC sequestration into the soil is steep over the 33 years considered. Moreover, comparing the results obtained for the two scenarios hypothesized for continuous corn and continuous wheat, it seems that with the second scenario the two systems will have the chance to have a higher SOC sequestration increase compared to manure supply for 26 years and crop residues incorporation for 7 years. This outcome is likely attributable to the disparate impact that these two agricultural practices exert(manure supply +crop residues incorporation and inclusion of alfalfa in the rotation) could have on soil dynamics and microbial activities related to the C cycle and SOC sequestration. This discrepancy is further compounded by the absence of tillage when alfalfa is cultivated.

3.3 Advantages and disadvantages of using mathematical models for determining CF contribution to future C sequestration

The ICBM model has proved to be an effective and relatively simple tool, being adaptable to site characteristics and measured data. The utilization of Bayesian statistics for model calibration permits us to include in the model the errors deriving from previous parameters estimation and data. Indeed, parameters definition results in being the most complex process because there are not many references in literature to estimate the errors and the selection of values associated to each parameter, to some extent, implies sometimes a modeler's choice. Thus, using the probability distribution of the parameters instead of fixed values, the model results to be more objective.

The use of the model for future predictions can be considered a practical tool to evaluate possible consequences on SOC sequestration deriving from the agronomic choice. Clearly, this use of the model gives only some indications and strictly depends on which information is given to the model (for exampledata input (e.g., climatic variations, crops rotation, yield, and external input).

In conclusion, from obtained results it is possible to state that mathematical models are practical tools for making assessments over time regarding carbon sequestration dynamics when different Carbon Farming techniques are applied and compared.

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