frontiers in Environmental Science

ORIGINAL RESEARCH
published: 29 November 2018
doi: 10.3389/fenvs.2018.00144

Soil C Storage Potential of Exogenous Organic Matter at Regional Level (Italy) Under Climate Change Simulated by RothC Model Modified for Amended Soils

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Specialty section:
This article was submitted to Soil Processes, a section of the journal Frontiers in Environmental Science

Received: *14 August 2018*
Accepted: *08 November 2018*
Published: *29 November 2018*

Citation:
Mondini C, Cayuela ML, Sinicco T, Fornasier F, Galvez A and Sánchez-Monedero MA (2018) Soil C Storage Potential of Exogenous Organic Matter at Regional Level (Italy) Under Climate Change Simulated by RothC Model Modified for Amended Soils. Front. Environ. Sci. 6:144. doi: 10.3389/fenvs.2018.00144

Soil amendment with exogenous organic matter (EOM) represents an effective option for sustainable management of organic residues and enhancement of soil organic C (SOC) content. Optimization of soil amendment is hampered by the high variability in EOM quality and pedoclimatic conditions. A possible solution to this problem could be represented by spatially explicit soil C modeling. The aim of this study was the evaluation at regional level of the long term C storage potential of EOM added to the soil under climate change by using a modified version of the RothC specifically developed for C simulation in amended soil. To achieve this goal a spatially explicit version of the modified RothC model was deployed to assess at a national scale the potential for C storage of agricultural soils amended with different EOMs. Long term model simulations of continuous amendment (100 years) indicated that EOMs greatly differ for their soil C sequestration potential (range 0.110–0.385 t C ha^{-1} y^{-1}), mainly depending to their degree of stabilization. Spatial explicit modeling of amended soil, taking into account the different combinations of EOMs and application sites, indicated a high variability in the potential of SOC accumulation at the national level (range: 0.06–0.62 t C ha^{-1} y^{-1}). EOM quality showed a larger impact on long term SOC accumulation than variability in pedoclimatic conditions. Model simulations predicted that the contribution of soil amendment in tackling greenhouse gas (GHG) emissions is limited: soil C sequestration potential of compost applied to all Italian agricultural land corresponded to 5.3% of the total annual GHG emissions in Italy. Large scale modeling enables areas with the largest potential for EOM accumulation to be identified, therefore suggesting ways for optimizing resources. The spatially explicit version of the modified RothC model improves the predictive power of SOC modeling at regional scale in amended soils, because it takes into account, besides variability in pedoclimatic conditions, the large differences in EOMs quality.

Keywords: organic residues, soil organic matter, soil C sequestration, soil C models, regional modeling, RothC model

INTRODUCTION

Exogenous organic matter (EOM) is all organic material of biological origin applied to the soil in order to fertilize, amend or restore it and improve the environment (Marmo et al., 2004). At European level, about 1,200 million tons of EOMs are produced each year (with exclusion of crop residues), while the annual production of EOMS in Italy is about 150 million tons.

The potential for soil amendments to recover and enhance soil organic matter (SOM) content, increase soil fertility and reduce soil degradation and atmospheric greenhouse gas (GHG) concentrations makes soil application of EOM attractive for both climate change mitigation and soil ecosystem sustainability (Lal, 2004; Smith, 2004a,b; DeLonge et al., 2013). The agricultural utilization of organic amendments is further stimulated by enhanced social awareness about the importance of protecting the environment and by legislative and economic drivers.

Soil amendment is indeed an attractive and effective option for solving the problems associated with EOM management, while favoring at the same time the recovery and building-up of soil organic C (SOC) stocks through the process of soil C sequestration (Karhu et al., 2012). In fact, in the last decades, significant SOC losses, mainly attributed to the cultivation of new land and the intensification of agricultural practices, have been recorded worldwide, with relevant consequences for both soil fertility and climate change (Lal, 2004). Soil C sequestration is defined as long-term (i.e., >100 years) or permanent removal of CO_2 from the atmosphere and its "lock up" into the soil (Stockmann et al., 2013). The long term sequestration of added EOM-C is likely to have remarkable positive impacts on soil quality, ecosystem functioning, climate change, and economical sustainability (Lal et al., 1998; Dumanski, 2004; Powlson et al., 2011). The rate of potential C sequestration by soil amendment in European soils has been estimated at 0.42 t C ha^{-1} y^{-1} (Smith et al., 2008) and 0.40 t C ha^{-1} y^{-1} by Freibauer et al. (2004). Arrouays et al. (2002) evaluated the potential rate for C sequestration of compost to be in the range 0.23–0.55 t C ha^{-1} y^{-1} for a period of 20 years of application.

However, the effects of EOM application on SOC stocks are very difficult to predict and markedly differing C dynamics have been recorded in long term experiments of soils amended with contrasting EOMs (Bipfubusa et al., 2008). The difficulty to predict long term SOC trajectory in amended soil is related to different factors such as the huge variability in the composition and properties of EOM, the slow change and high spatial variability of SOC and the marked differences in soil properties and environmental conditions.

EOM includes organic residues from agricultural, urban and industrial origin, as well as, the products of their processing (Marmo et al., 2004). As such EOMs encompass an extremely wide range of bio-wastes from a considerable variety of sources. EOMs may have various forms (solid, liquid, pasty) and undergo different treatments before application to the soil. As a consequence, the EOMs potentially applicable to soil present highly variable physicochemical characteristics and therefore can affect the soil ecosystem in different and unpredicted ways (Cayuela et al., 2010). In addition, SOC changes in soil are usually very slow and in temperate regions it is normal that SOC variations are not statically relevant even 10–20 years after a significant change in land management. Finally, soil physical, chemical and biological properties, climatic conditions and land use and management are other important factors affecting the rate of EOM mineralization (Franzluebbers, 2004).

The high uncertainty regarding the amount of EOM-C that would ultimately accumulate in the soil and the lack of a thorough knowledge of the processes involved in EOM mineralization (Foereid et al., 2014) make difficult to consider amendment in global SOC assessments and among the internationally agreed measures to tackle climate change. In fact, the prerequisite for developing policies for increasing SOM by organic amendments is the availability of data and/or tools that can be used to demonstrate variations in C stocks due to changed management and therefore it is of upmost relevance to assess the potential and variability in C sequestration of EOMs. Long term filed experiments are the ideal tool for detecting and quantifying slow change in SOC in amended soils, but it is not feasible to conduct long term experiments covering all the possible combinations of climate and management options and providing results within a reasonable time. Moreover, measuring changes in soil C stocks by repeated measurements is time consuming and expensive (Mäkipää et al., 2008). Soil C models represent an effective and feasible solution to this problem as they can predict SOC stocks, anticipate probable trends in SOC and estimate the long term C sequestration potential of EOMs under many different combinations of soils, environmental conditions, land use and managements and climate change scenarios (Powlson, 1996).

Two main limitations hamper SOC model application to amended soil.

The first one is represented by the fact that actual models do not adequately describe the high variability in EOMs quality. Recently, a modified version of the widely known and validated RothC model, specifically aimed to amended soil, has been proposed and developed to overcome this limitation (Mondini et al., 2017).

Secondly, SOC organic C models are generally point based and perform simulation of SOC one site at a time. However, to support land managers and policy makers to design future soil management options aimed to restore and enhance SOM, more detailed spatially explicit information by SOC modeling is required. This can be achieved by connecting Geographic Information Systems (GIS), which contain detailed spatial information on soils, climate, land use, and management, with a state-of-the-art SOC model. Spatially explicit SOC modeling is used to quantify existing soil C stocks, predict changes in soil C as a function of several scenarios of pedoclimatic conditions and land use and management and assess likely responses to climate change (Paustian et al., 1997). Application of SOC models at the regional scale enables the pedoclimatic conditions and land use to be taken into account, makes it possible to analyse the effect on SOC stocks of the interaction of soil properties, weather characteristics and land-use and management and to identify areas with larger potential for C storage.

To date, large scale applications of SOC models have mainly dealt on the effects of land-use change. As an example the integration of the RothC model with soil land use and climate data in a GIS environment was successfully illustrated by Abegaz et al. (2016) for Ethiopia, Bleuler et al. (2017) and Farina et al. (2017) for Mediterranean regions, Falloon and Smith (2002), Smith J. et al. (2005), Smith et al. (2006), and Falloon et al. (2006) for European cropland grassland and forest, Smith et al. (2007) for European Russia, Parshotam et al. (1995) for New Zealand, Wan et al. (2011) for China, and Jones et al. (2005) at global level. However, information on the spatial variability of C stocks in contrasting soil amended with different EOMs is limited to few studies (Mondini et al., 2012; Bleuler et al., 2017). Since SOC storage of EOM added to the soil is controlled by a variety of biogeophysical, climatic and management factors, dynamic models, which integrate the main mechanisms governing SOC turnover, with information on the spatial variability of such factors, are the most suitable tool for predicting SOC changes at regional level due to the application of contrasting EOMs. Large scale regional modeling of SOC in amended soils could provide useful information to predict the C sequestration and GHG emissions offsetting potential of EOMs, identify the relative importance of the different factors in the SOC evolution observed and highlight the combination of factors more conducive to the soil storage of added C. This in turn would allow planning land use management and agronomical practices enhancing soil C sequestration. Moreover, it is important to note that methods leading to reliable, transparent and verifiable changes in soil C stock at regional level are necessary for the inclusion of soil C sequestration from agricultural soils and land use changes among the measures internationally allowed under the Kyoto Protocol. Finally, as EOM availability is generally limited with respect to the land suitable for amendment, large scale spatial modeling of soil organic C can suggest ways to optimize such resources by identifying the areas with the greatest potential for the accumulation of SOC from EOM.

The aim of this study was the application of the RothC model, modified and optimized by Mondini et al. (2017) for amended soils, for the evaluation of long term SOC storage potential of EOM at regional scale under climate change.

More specifically the aims were to:

- deploy a spatially explicit version of the modified and optimized Roth C model
- estimate the long term potential for soil C storage and GHG offsetting of contrasting EOM added to the soil at a national scale (Italy) under climate change
- evaluate the variability in the projected long term changes of SOC in Italian amended soils
- identify area with major potential for C sequestration by soil amendment
- elucidate the relative importance of EOM quality and pedoclimatic conditions on the soil C sequestration potential of added C.

MATERIALS AND METHODS

This study is based on the application of the RothC model, modified by Mondini et al. (2017), to the long term modeling of SOC in EOM treated soils at regional level under climate change. Detailed information on model features, modification to the model structure and procedure utilized for the calibration of the EOM pools parameters is reported in the work of Mondini et al. (2017).

Briefly, the model structure was modified by introducing additional pools of decomposable (DEOM), resistant (REOM), and humified (HEOM) EOM, each characterized by specific partitioning factors (f) and decomposition constant rates (K; unit: y^{-1}). The parameters of the additional EOM pools were estimated by model fitting to respiratory curves of amended soils incubated in the laboratory. For the laboratory incubations 30 different EOMs classified in 8 EOM groups (compost, code: CO; bioenergy by-products, BE; anaerobic digestates, AD; meat and bone meals, MM; animal residues, AR; crop residues, CR; agro-industrial wastes, AW; sewage sludges, SS) were utilized (Mondini et al., 2017). CO, AD, and AW were considered to be characterized by 3 EOM pools (DEOM, REOM, and HEOM), the remaining EOM groups by 2 pools (DEOM and REOM).

In the present study, the modified and optimized model was first tested for sensitivity toward variations in EOM pool parameters and generality, i.e., the adaptability to simulate SOC in soils amended with various EOM utilizing a common set of parameters. Successively, a spatially explicit version of the model was deployed that was applied to the long term simulation of SOC in amended soil at national level (Italy).

Sensitivity Analysis

To study the sensitivity of SOC values predicted by the modified RothC model to the different quality of EOM inputs over the experimental timescale, a model exercise was performed utilizing weather (average climate data for 1901–2000) and land management data for the S. Martino arable soil (WRB: Calcari-Fluvic Cambisol, sand 69%, clay 3%, pH 8.3, SOC 1.0%, N_{TOT} 0.12%) located in NE Italy at 46° 1′ N 12° 53′ E. Data relative to weather and land use and management are described in section Data Sets.

After an equilibrium run, the model was run for 100 years utilizing the same model inputs, but assuming a yearly addition of EOM at a rate of 1 t C ha y^{-1}. Two scenarios were simulated, i.e., addition of mixed swine bovine meat and bone meal (SB) and household waste compost (HWC). Properties of EOMs are reported in Mondini et al. (2017). For each EOM, model runs were performed utilizing initial values of the parameters derived from a model parameterization under standard laboratory incubation conditions (defined as: 20°C, 40% water holding capacity (WHC), 0.5% w:w EOM application rate and 30 days incubation period) and then individually varying each parameters at arbitrary values, while maintaining constant the other parameters. A sensitivity index (SI) was calculated according to Ng and Loomis (1984) as:

Sensitivity index (SI) = % change in output variable/% change in input variable

The input variables were f_{DEOM}/f_{REOM}; f_{DEOM}/f_{HEOM}; f_{REOM}/f_{HEOM}; K_{DEOM} and K_{REOM} (Mondini et al., 2017), while the variation in SOC with respect to the baseline (SOC at equilibrium) was considered as the output variable. A large value of SI indicates that the model output variable is relatively insensitive to changes in the input variable; a small SI value indicates that the model output variable is sensitive to changes in the input variable. A SI value of 1 indicates that changes of 1% in the input value result in a change of 1% in the output variable. Negative SI values indicate that increasing the input value decreases the output value; positive SI values indicate that increasing the input value increases the output value.

Generality Tests

The aim of the test was to evaluate the degree of generality of the modified model by looking at the difference in long term SOC simulation when using specific and common sets of EOM parameters.

The test was performed assuming a scenario of soil amendment at a rate of 1 t C y^{-1} for 100 years (2001–2100) to the S. Martino soil. For each of the EOM groups defined in Mondini et al. (2017), a common set of EOM parameters was defined by calculating the average of parameters for all the EOMs included in the group. Therefore, a long term simulation using this common set of parameters was compared to a simulation performed utilizing EOM-specific parameters obtained from incubation under laboratory standard conditions (20°C temperature, 40% WHC, 0.5% w:w rate of EOM application, 30 days of incubation). Such comparison was performed for each EOM type included in the EOM group.

The degree of generality was evaluated by looking at the percent difference of SOC accumulation after 100 years of EOM addition between simulations utilizing specific and common (i.e., mean) model parameters.

Long Term Modeling of Amended Soils at Regional Level Under Climate Change

Data Sets

The geographic window, within which the study was performed, covers the area: longitude 6.750–18.417 E, latitude 36.750–46.917 N. The GIS platform used was ARC Map 9.3.

Information on soil properties and spatial distribution and land use classes were derived from the Soil Geographical Database of Europe (SGDBE) (European Soil Database Distribution Version, 2004). The database represents a digital version of the 1:1,000,000 Soil Map of Europe and presents geometric and semantic components, soil information being presented in the form of Soil Map Units (SMUs), with each polygon unit on the map being assigned to a single SMU. Each SMU comprises a number of soil types or Soil Typological Units (STUs) which are associated together within the SMU landscape, but cannot be separated spatially at the 1:1,000,000 map scale. The number of SMU polygons for Italy was 1,314.

Weigthed average SOC stocks (t C ha^{-1}) and clay content (%) to fixed depth (25 cm) were derived from SPADE2 soil profile analytical database for Europe (Hannam et al., 2009). To calculate SOC stocks at fixed depth (25 cm) the SOC stocks of horizons included within the first 25 cm were composited using weighted averaging according to the following equation:

$$\mathrm{SOC_{25cm}}(\mathrm{t\ ha^{-1}}) = \Sigma \mathrm{OC_i} \times \mathrm{BD_i} \times \mathrm{h_i} \tag{1}$$

Where OC = organic C (%), BD = bulk density (g cm^{-3}), h = soil depth (cm) for the i^{th} horizon included within the first 25 cm.

SPADE 2 was developed to be used in conjunction with the SGDBE database, providing the soil property data for each STU. The window contained 295 representative soil profiles.

SPADE2 also provides the dominant and secondary (when present) land use class according to the Corine Land Cover nomenclature for each STU. In the database 22 different land class uses are present of which 10 were present in the STU associated with Italy. Of these, 6 represent agricultural land uses classes (grassland, arable, horticulture, vineyards, olive trees, and industrial crops), covering 63.8% of the total land.

Monthly temperature and precipitation data for Italy were extracted from CRU 1.0 (for the range 1901–2000) and TYN SC 1.2 (for the range 2001–2100) European climate databases at a 10′ × 10′ resolution downloaded from the Climate Research Unit of the University of East Anglia (Mitchell et al., 2004). The climate data for the geographic window (Italy) were extracted utilizing the TETYN software (Solymosi et al., 2008).

Monthly climate values for 2001–2100 were provided using outputs from 3 different Global Circulation Models (GCMs), namely HadCM3, PCM, and GCM2 (Mitchell et al., 2004), forced by 4 different CO_2 emissions scenarios, A1FI, A2, B1, B2, as defined in the IPCC Special Report on Emissions Scenarios (SRES) (Nakicenovic et al., 2000) for a total of 12 different climate scenarios (Nakicenovic et al., 2000; Smith and Powlson, 2003). The emissions scenarios estimate future concentrations of GHG in the atmosphere to which climate is sensitive based on assumptions about patterns of economic and population growth, technology development and other factors.

Monthly potential evapotranspiration (ET) for each point of the 10′ × 10′ grid for the 1901–2100 period were calculated from temperature, precipitation and diurnal temperature range data according to the Hargreaves method (Allen et al., 1998).

For the modeling exercise, averaged monthly values of climatic data for the period 1901–2000 and averaged decennial values for the period 2001–2100 were utilized.

Point layers containing the meteorological data were created in ArcMap with each layer consisting of 1,191 grid points.

Layer Linkages

An ArcMap built-in functionality was utilized to find the center of all SMU polygons. The SMU centers were then linked through a spatial join to the nearest point of the meteorological layer, resulting in a linked soil mapping unit/meteorological layer constituted by 1,314 polygons. The SMU/climate layer were then linked with the soil and land use data through a query operated in MS Access utilizing information provided by the geographic and semantic components of SGDBE. This provided a linked soil, land use and meteorological database constituted by 10,130 rows representing a unique combination of soil, land use, and meteorology (Falloon et al., 1998b, 2002). Simulations were performed for each of the 10,130 combination of climate and soil data.

Running the Modified RothC Model

RothC input and setup files were created for each one of the unique 10,130 combinations of soil, land use, and meteorology data. For each combination, the initial C content of the different SOC pools and the annual plant addition to the soil were obtained by running the RothC model to equilibrium (Coleman and Jenkinson, 1996) using average climate data for 1990–2000 and by using the clay and SOC content provided by the SPADE2 database.

The monthly distribution of plant input was calculated in two stages. Initially, the total annual plant input was assumed to be 1 t C ha^{-1} and the proportions of plant material added to the soil in each month were set to describe the typical pattern of inputs for each land use class. After RothC was run to equilibrium, the annual C input from plant residues was adjusted to give the measured soil C content provided in the soils database using the following equation:

$$P_{req} = P_i \times [(C_{meas} - IOM)/(C_{sim} - IOM)] \quad (2)$$

where P_{req} is monthly C input, P_i is the initial monthly total C addition (the sum of the proportions of the C input in the first equilibrium run is 1), C_{meas} is the measured soil C given in the soils database, C_{sim} is the simulated soil C after the equilibrium run, and IOM is the C content of the inert organic matter fraction in the soil (all in t C ha^{-1}). The size of the IOM fraction was set according to the equation given by Falloon et al. (1998a):

$$IOM = 0.049 \times C_{meas}^{1.139} \quad (3)$$

Having determined the plant additions and C contents of SOC pools, the simulations were run between 2001 and 2100 using the predicted climate and land use data.

Two predicted land management scenarios were chosen for estimation of C sequestration potential: annual addition of EOM at a rate of 0 (baseline) and 1 t C ha^{-1}.

The model was run for each of the EOM groups (compost, bioenergy by-products, anaerobic digestates, meat and bone meals, animal residues, crop residues, agro-industrial wastes, sewage sludges) defined in Mondini et al. (2017) utilizing mean EOM parameters calculated from all the EOMs included in the group. The model was run to the year 2100 for the 12 climate scenarios considered and for the two land management scenarios described above, giving 108 combinations of EOM groups × climate scenarios × management scenarios. For each polygon, the change in SOC under the baseline run was subtracted from the change in SOC under a land management scenario including EOM addition to give the net soil C sequestration due to the change in land management.

Application of EOM was only considered for agricultural land use classes. Soils with natural land use classes were therefore excluded from the simulations. Similarly, organic soils with a SOC content >200 t ha^{-1} were also excluded from simulation as RothC has not been parameterised for organic soils (Coleman and Jenkinson, 1996). Consequently, land for which EOM addition was simulated was 60% of total constituted by a linked soil database of 7,392 unique combination of soil, land use, and meteorology.

On the basis of the simulations performed for the whole agricultural land, further simulations were performed by applying EOMs to either the land with the greatest or lowest C storage potential. The area interested in the simulation was estimated on the basis of the predicted total production of compost in Italy for the year 2020 (1,800,000 t; CIC-Italian Composting Biogas Association, 2010). According to mean analytical data for compost produced from food wastes (CIC-Italian Composting and Biogas Association, 2000) and an application rate of 1 t C ha^{-1} y^{-1}, this amount could be spread on 213,750 ha of agricultural land. Therefore, model runs were performed for the climate scenarios PCM B1 and GCM2 A1FI simulating 100 years of annual additions of two different EOMs (compost and meat and bone meal) to 213,750 ha of either the area with the greatest or lowest potential for C sequestration, as determined by simulations performed on the whole agricultural land.

Data Treatment

Model runs were performed for each combination of STU and Land Use within each SMU. This was done in order to obtain the higher amount of information possible from the available data.

However, the SPADE database does not provide information on the percentage of land covered by each land use classes. Conversely this information is provided for each STUs within the corresponding SMU, however STUs cannot be separated spatially at the 1:1,000,000 map scale. Therefore, for visualization it is necessary to obtain a reduction of available information at SMU level. This was obtained for SOC utilizing the following criteria:

Land use: the fraction of STU area that is occupied by their defined dominant and secondary land use was estimated according to Hannam et al. (2009). In the case of STU presenting only the dominant land use that use was attributed to 80% of the total area of the STU. In the case of STU presenting both dominant and secondary land use it was assumed that the STU is covered by 60% from the dominant land use and 30% from secondary land use.

STU: SOC content of each SMU was calculated operating a weighted average of the C content of each STU, considering the STU's percent area distributions within the SMU reported in the SGDBE database.

Uncertainty

Uncertainty analysis was performed to evaluate the effect of EOM quality on model output. For this aim, long term simulation runs were performed utilizing weather (average climate data for the period 1901–2000) and land management data for the S. Martino soil. After an equilibrium run, the model was run for 100 years utilizing the same model inputs, but assuming a yearly addition of EOM at a rate of 1 t C ha y^{-1}. The evaluation of the influence of the variation in the model input on the output was performed with one-at-a-time analysis, where the input parameter was varied within the range of its variability, while all other inputs were kept constants. The input parameters considered for uncertainty analysis were partitioning factors and decomposition rates of EOM pools, while the output value was the EOM C sequestered at the end of the simulation period (i.e., SOC in amended soil minus SOC in the unamended soil). For each pool parameter and EOM-group, runs were performed utilizing the average, maximum and minimum value of the parameter resulting from the optimization procedure, considering such parameter values as probability distributions for input variables, e.g., the range of values that such parameter can assume. The uncertainty in C sequestration potential for the different EOM groups was expressed by the standard deviation of the different estimates of C sequestration using the range of pool parameters derived from the optimization procedure. The uncertainty of prediction in C storage potential associated to the different inputs was expressed as the percentage change in the C sequestered at the average pool parameter value (Smith et al., 2014).

RESULTS

Sensitivity Analysis of Modified Model

Two contrasting EOMs were selected to test the modified model sensitivity to the variation in the parameters defining EOM quality, namely mixed swine bovine meat and bone meal (SB) and household waste compost (HWC).

In the case of SB, characterized by two EOM pools, DEOM and REOM, the parameter presenting the greatest effect on the simulated SOC was K_{REOM} (**Figure 1**; **Table S1**). The SI index was negative indicating an inverse relationship between the parameter and the output. Moreover, SI for K_{REOM} was not constant and displayed the lowest absolute values in correspondence to the lowest values of K_{REOM}. Consequently, SOC values predicted with RothC are more sensitive to differences in K_{REOM} at smaller values of the parameter. The model output was sensitive to K_{DEOM} only at very low values (<1). The model displayed a moderate sensitivity to variations in the f_{DEOM}/f_{REOM} ratio. Variation of the ratio from 9 to 0.11 resulted in 2.4 C t ha^{-1} increase, with larger differences at lower values of the ratio.

In the case of EOM characterized by 3 pools, typically the composted substrates, the most influential parameter on the model output was the f_{REOM}/f_{HEOM} ratio, especially at lower values (i.e., high contents of humic-like substances) (**Figure 2**; **Table S2**). The model output was also sensitive to variations in the f_{DEOM}/f_{HEOM} ratio; such sensitivity was higher at low values of the ratio. Variations in K_{REOM} presented a moderate effect on the model output. Changing the value from 0.75 to 0.15 resulted in a SOC increase of 2.31 t C ha^{-1}, corresponding to 3.3% of the initial value.

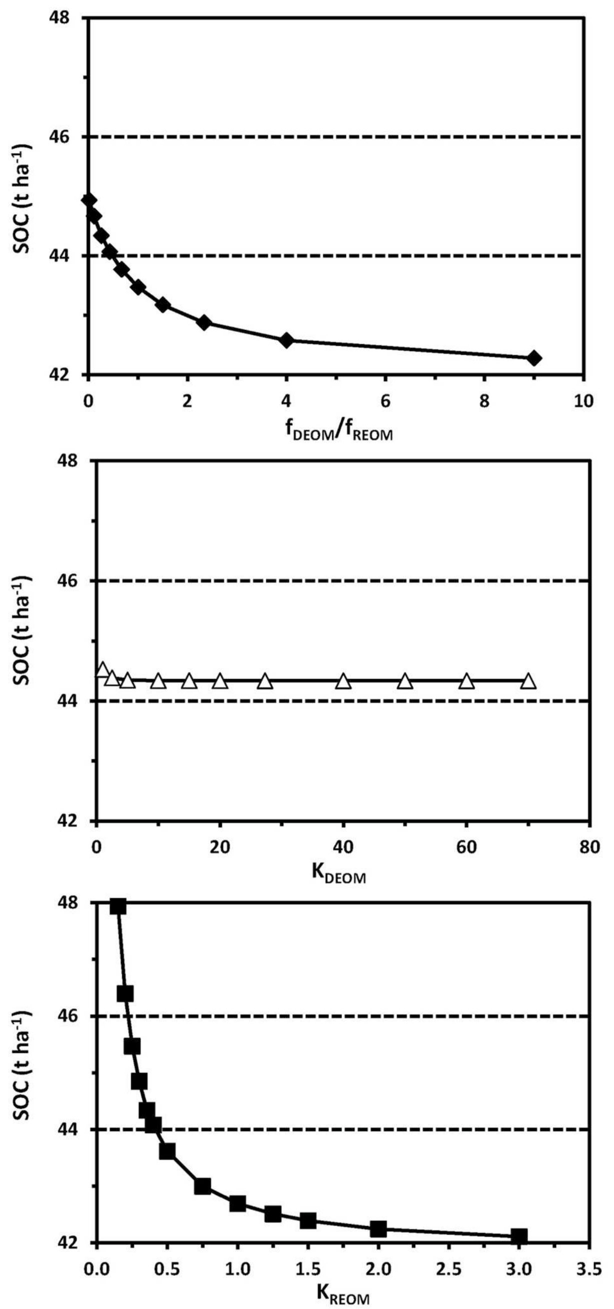

FIGURE 1 | Roth C EOM pool parameters sensitivity analysis for meat and bone meal amended soil.

Generality Test of Modified and Optimized Model

The results of the generality test are reported in **Table 1** and show that the difference in terms of SOC accumulation between simulations of 100 years of consecutive EOM addition at a rate of 1 t C ha^{-1} y^{-1} carried out with common and specific sets of EOM parameters was in the range −9.2 to 4.7%, i.e., the absolute error in SOC by taking the EOM-group mean parameters instead of the specific EOM-type was <10%. The EOM group showing the larger variability between simulations performed with common and specific sets of EOM parameters was compost.

Long Term Modeling of Amended Soil

Climate Change

Variations in temperature, precipitation and ET for Italy, between 2001 and 2100, foreseen by the 12 different climate scenarios used for the model simulations are reported in **Table 2**. The temperature in 2100 was anticipated to increase on average by

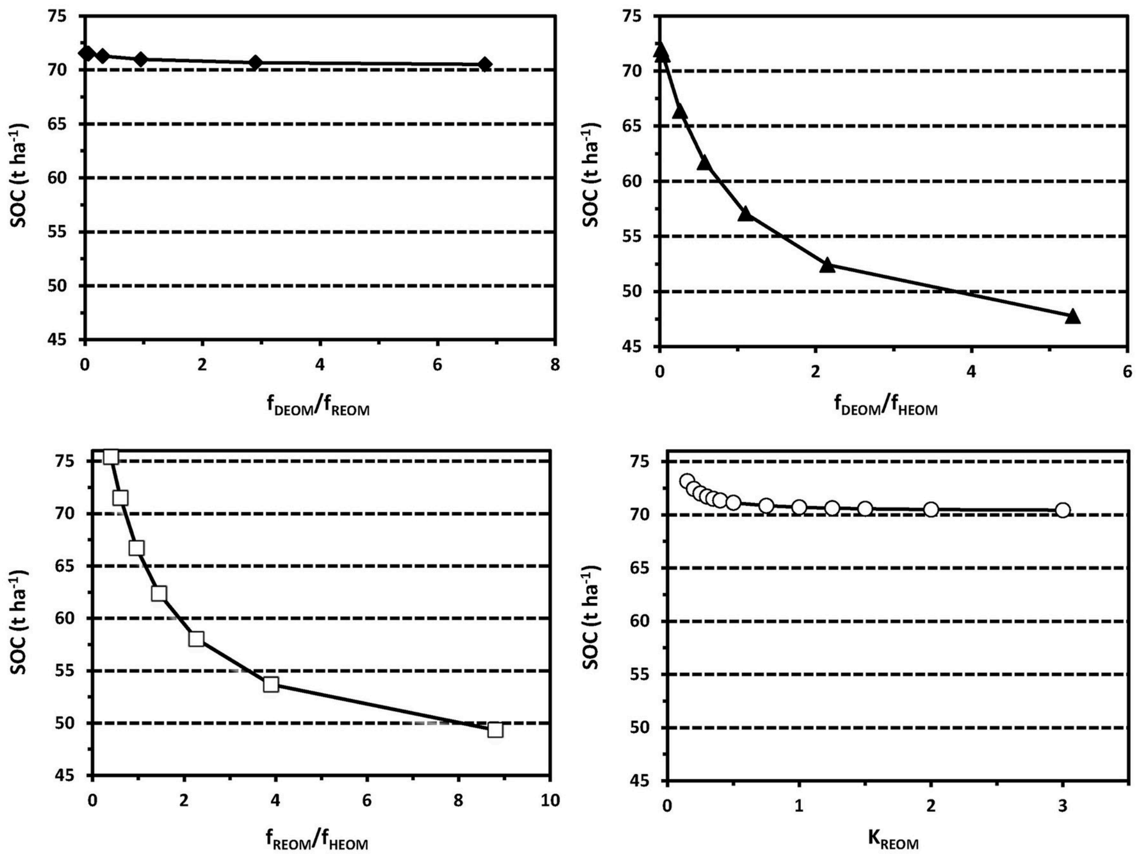

FIGURE 2 | Roth C EOM pool parameters sensitivity analysis for household waste compost amended soil.

3.2°C (range 1.5–6.0°C) with respect to the baseline (2001). Similarly, ET was also predicted to increase, on average, by 14.1 mm month^{-1} (range 5.7–28.6 mm month^{-1}). On the whole, precipitation slightly decreased by 1.7 mm month^{-1}, although there were significant distinctions among climate scenarios, as the variations in precipitation ranged from negative (−7.7 mm month^{-1} for HadCM3 A1FI) to slightly positive (1.9 mm month^{-1} for GCM2 B1). HadCM3 A1FI was the climate scenario showing the largest variation with respect to the baseline, while PCM B1 was the one presenting the lowest change. Considering the SRES emissions scenarios, A1FI and B1 showed the largest and smallest increase of temperature and ET, respectively.

Potential C Sequestration and GHG Offsetting of Soil Amendment

The results of the simulations performed at national scale with the model optimized for 8 different EOM groups and 12 climate scenarios are reported in **Table 3**. The 8 EOM groups significantly differed for their potential to build-up SOC stocks. Yearly C sequestration potential varied from 0.110 to 0.385 t C ha^{-1} y^{-1} for meat and bone meal and compost treated soils, respectively. Exogenous organic matter quality had a great impact on the proportion of added C ultimately remaining in the soil, as the same amount of added C resulted in a 3.5-fold difference in SOC sequestration potential. The largest C sequestration was predicted in compost amended soil, while the smallest was anticipated in the soil amended with meat and bone meals and animal residues. Bioenergy by-products showed values of yearly sequestration rates very similar to animal residues (0.121 t C ha^{-1} y^{-1}). A good potential for SOC sequestration was recorded for anaerobic digestates (0.262 t C ha^{-1} y^{-1}) and agro-industrial waste (two-phase olive mill waste) (0.203 t C ha^{-1} y^{-1}).

A significant power correlation was found between the cumulative respiration of amended soil under standard laboratory conditions (Mondini et al., 2017) and the mean potential for C sequestration of each EOM group (**Figure 3**).

For each EOM group, the variability in the potential to build up SOC stocks considering all the combination of soil, land use and climate data at the national level (7,392 combinations) was very large. As an example, in the case of the compost group, minimum and maximum annual SOC increases were 0.22 and 0.62 t C ha^{-1} y^{-1}, respectively. Considering all the combinations between the different EOM groups and the application sites, the variability in the potential C sequestration further increased, spanning over 1 order of magnitude (range 0.06–0.62 t C ha^{-1} y^{-1}).

The variations among the different future climate scenarios utilized in this study had a moderate effect on the C sequestration

TABLE 1 | Results of RothC generality test: simulation of 100 years of amendment utilizing EOM-type and EOM-group pool parameters.

EOM group	EOM type	EOM Code	f_{DEOM}	f_{REOM}	f_{HEOM}	K_{DEOM}	K_{REOM}	SOC t C ha^{-1}	Difference m-s (%)
Compost (CO)	Vine shoots compost (VSC)	VSC_CO_s	0.02	0.39	0.59	45	0.35	70.6	−3.4
	Household waste compost (HWC)	HWC_CO_s	0.02	0.37	0.61	43	0.35	71.5	−4.6
	Green waste compost (GWC)	GW_CO_s	0.01	0.52	0.47	200	0.42	65.2	4.7
	Straw/cotton cardings/meat and bone meal compost (CMC)	CMC_CO_s	0.00	0.31	0.69	105	0.36	75.1	−9.2
	Straw/cotton cardings/meat and bone meal/hoof and horn meal compost (CBC)	CBC_CO_s	0.01	0.35	0.64	99	0.38	72.8	−6.2
		CO_m	0.03	0.44	0.53	79	0.30	68.2	
Bioenergy by-products (BE)	Bioethanol residue (BR)	BR_BE_s	0.12	0.88		147	0.68	43.3	3.6
	Rape seeds meal (RSM)	RSM_BE_s	0.11	0.89		44	0.32	45.0	−0.4
		BE_m	0.13	0.87		92	0.33	44.8	
Anaerobic digestates (AD)	Pig slurry digestate (PS)	PS_AD_s	0.08	0.62	0.30	26	0.15	60.6	−4.8
	Two-phase olive mill waste digestate (OW)	OW_AD_s	0.01	0.83	0.16	64	0.17	54.9	5.0
		AD_m	0.02	0.73	0.25	220	0.20	57.7	
Meat and bone meals (MM)	Bovine meat and bone meal (BV1)	BV1_MM_s	0.16	0.84		66	0.23	46.0	−4.4
	Mixed swine bovine meat and bone meal (SB)	SB_MM_s	0.21	0.79		27	0.36	44.3	−0.7
	Bovine meat and bone meal (BV2)	BV2_MM_s	0.16	0.84		75	0.18	47.2	−6.8
	Defatted bovine meat and bone meal (DE)	DB_MM_s	0.20	0.80		68	0.16	47.6	−7.6
		MM_m	0.21	0.79		74	0.41	44.0	
Animal residues (AR)	Hydrolyzed leather (HL)	HL_AR_s	0.13	0.87		28	0.58	43.5	1.6
	Blood meal (BLM)	BM_AR_s	0.04	0.96		132	1.20	42.7	3.6
	Horn and hoof meal (HHM)	HHM_AR_s	0.33	0.67		14	0.15	47.0	−6.1
		AR_m	0.15	0.85		110	0.41	44.2	
Crop residues (CR)	Cotton cardings (CC)	CC_CR_s	0.08	0.92		32	0.16	48.5	−5.4
	Wheat straw (WS)	WS_CR_s	0.08	0.92		37	0.17	48.1	−4.6
		CR_m	0.05	0.95		63	0.27	45.8	
Agro-industrial wastes (AW)	Two-phase olive mill waste (TPOMW)	TPOMW_AW_s	0.05	0.76	0.19	132	0.31	53.5	−2.7
		AW_m	0.04	0.78	0.19	126	0.56	52.0	
Sewage sludges (SS)	Wastewater sewage sludge (WW)	WW_SS_s	0.04	0.96		45	0.31	45.3	3.3
		SS_m	0.04	0.96		63	0.22	46.8	

EOM, exogenous organic matter; f, partitioning factor; K, decomposition constant; DEOM, decomposable EOM; REOM, resistant EOM; HEOM, humified EOM; s, model parameters derived from EOM-type specific incubation under standard conditions; m, model parameters derived from the mean of all the incubations for the EOM group. Simulation scenario: 100 years of EOM addition at 1 t C ha^{-1} y^{-1}.

potential predicted by the model for the different EOMs. The coefficients of variation (c.v.) of mean yearly sequestration potential for the 12 climate scenarios were in the range 2.1–3.8% depending on the EOM group (**Table 3**). The variability was larger among SRES emission scenarios (c.v. range 1.9–3.5%) than among GCMs models (c.v. range 1.3–2.2%). Considering SRES emission scenarios, B1 was the one promoting the larger EOM C accumulation, while smaller sequestration potentials were recorded for A1FI.

A significant inverse relationship was found between the increase in temperature and evapotranspiration for each of the 12 climate scenarios and the soil C sequestration potential of

TABLE 2 | Variation in climate parameters for Italy between 2001 and 2100 for 12 different climate scenarios.

Climate parameter	HadCM3				PCM				GCM2				Mean
	A1FI	A2	B1	B2	A1FI	A2	B1	B2	A1FI	A2	B1	B2	
Temperature (°C)	6.0	4.9	2.9	3.4	3.2	2.7	1.5	1.9	4.2	3.5	1.9	2.4	3.2
Precipitation (mm month^{-1})	−7.7	−5.9	−4.9	0.0	−0.8	−0.4	−0.3	−1.0	−2.0	−1.3	1.9	1.8	−1.7
Evapotranspir. (mm month^{-1})	28.6	22.9	14.6	16.6	16.6	10.5	5.7	7.4	16.6	13.8	6.9	8.8	14.1

HadCM3, PCM, GCM2: general circulation climate models. A1FI, A2, B1, B2: emissions scenarios.

TABLE 3 | Modeled soil C sequestration potential for different EOM groups and climate scenarios in Italian agricultural soils amended for 100 years at a rate of 1 t C ha^{-1} y^{-1}.

GCM	SRES	EOM group										
	scenario	CO	BE	AD	MM	AR	CR	AW	SS	Mean	SD	CV
		SOC sequestration rate (t ha^{-1} y^{-1})										(%)
HADCM3	A1FI	0.375	0.116	0.253	0.106	0.108	0.129	0.197	0.141	0.178	0.095	53.1
	A2	0.378	0.118	0.256	0.107	0.109	0.131	0.199	0.144	0.180	0.095	52.8
	B1	0.395	0.126	0.271	0.114	0.117	0.141	0.210	0.156	0.191	0.098	51.4
	B2	0.383	0.120	0.261	0.109	0.111	0.134	0.202	0.147	0.183	0.096	52.3
PCM	A1FI	0.385	0.121	0.262	0.110	0.112	0.135	0.204	0.149	0.185	0.097	52.2
	A2	0.386	0.121	0.263	0.110	0.112	0.135	0.204	0.149	0.185	0.097	52.3
	B1	0.397	0.128	0.273	0.115	0.118	0.143	0.211	0.158	0.193	0.099	51.2
	B2	0.394	0.126	0.270	0.114	0.116	0.141	0.209	0.155	0.191	0.098	51.5
GCM2	A1FI	0.372	0.116	0.252	0.105	0.107	0.128	0.196	0.141	0.177	0.094	52.9
	A2	0.379	0.119	0.258	0.108	0.110	0.132	0.200	0.145	0.181	0.095	52.6
	B1	0.389	0.124	0.266	0.112	0.115	0.138	0.206	0.152	0.188	0.097	51.7
	B2	0.384	0.121	0.262	0.110	0.112	0.135	0.203	0.149	0.185	0.096	52.1
Mean		0.385	0.121	0.262	0.110	0.112	0.135	0.203	0.149	0.185		
SD		0.008	0.004	0.007	0.003	0.004	0.005	0.005	0.006			
CV (%)		2.1	3.3	2.6	3.1	3.1	3.6	2.3	3.8			

EOM, exogenous organic matter; GCM, general circulation climate model; SRES, special report on emissions scenarios; SD, standard deviation; CV, coefficient of variation; CO, compost; BE, bioenergy by-products; AD, anaerobic digestates; MBM, meat and bone meals; AR, animal residues; CR, crop residues; AW, agro-industrial wastes; SW, sewage sludges.

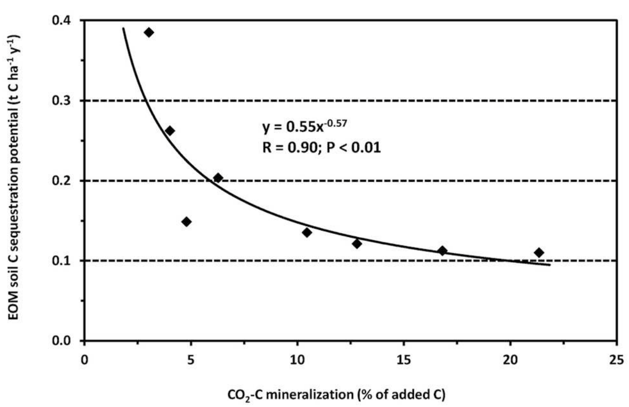

FIGURE 3 | Relationship between net CO_2-C mineralization and soil C sequestration potential for 8 different EOM groups.

amended soil (**Figure 4**). No significant relationship was found between changes in precipitation and C sequestration potential.

Regarding the soil C sequestration potential of soil amendment at national level, **Table 4** reports the total amount of SOC accumulated in the soil after 100 years of consecutive application of EOM at a rate of 1 t C ha^{-1} to all the area of agricultural land in Italy. Results showed a high variability in the average increase of SOC stocks ranging from 175 to 615 Mt (annual increase 1.75–6.15 Mt y^{-1}), depending on the EOM group. The percentage of increase with respect to the baseline varied from 25.1% for meat and bone meal to 88.6% for compost amended soils.

Spatially Explicit Modeling of SOC in Amended Soils

The procedure adopted in this work allows the intensity in SOC changes in amended soils due to variations in climate, land use and soil management to be visualized on a map. As an example, on **Figure 5** is reported a map of Italy showing the expected increase in SOC stocks (expressed in t C ha^{-1}) that could be achieved in 2100 due to repeated annual addition of compost to all agricultural land for a specific climate scenario (PCM B1). Areas with a SOC increase of 51–62 t C ha^{-1} are all located in the mountain areas of Northern Italy characterized by grassland land use. The places on the map with the SMUs having a SOC increase in the range 41–50 t C ha^{-1} are mainly situated in the eastern portion of Po valley. The main areas with an intermediate

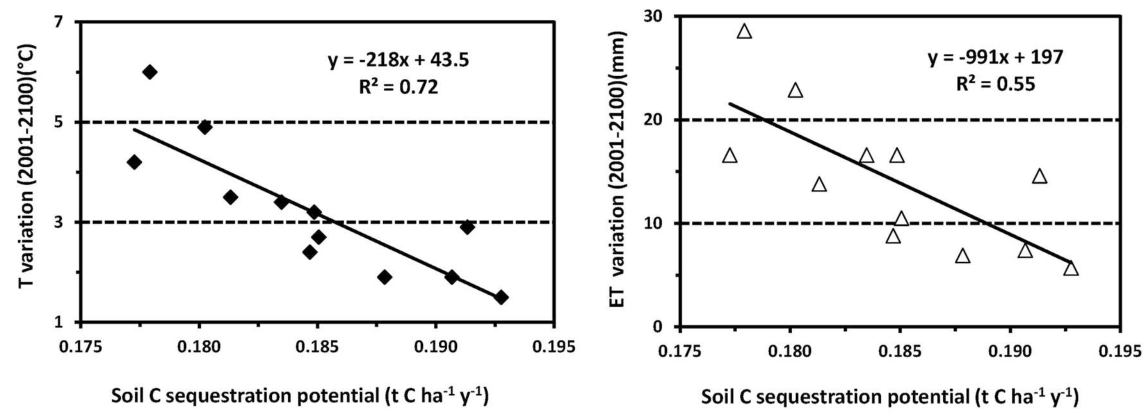

FIGURE 4 | Correlations between changes in temperature (T) and evapotranspiration (ET) predicted by 12 different climate scenarios between 2001 and 2100 and mean C sequestration potential of amended Italian agricultural soils.

TABLE 4 | Modeled total SOC (Mt) increment in Italian agricultural soils amended for 100 years at a rate of 1 t C ha^{-1} y^{-1} with different EOM groups and under different future climate scenarios.

SRES	GCM																										
scenario	HADCM3								PCM								GCM2										
	CO	BE	AD	MM	AR	CR	AW	SS	CO	BE	AD	MM	AR	CR	AW	SS	CO	BE	AD	MM	AR	CR	AW	SS	Mean	SD	CV
	SOC increment (Mt)								SOC increment (Mt)								SOC increment (Mt)										(%)
A1FI	600	184	404	168	171	204	316	223	620	193	420	176	180	215	327	236	592	182	398	166	169	201	312	220	287	146	50.9
A2	605	186	408	170	173	206	319	226	617	191	417	174	178	213	325	233	604	186	407	170	173	206	318	226	289	147	50.8
B1	634	200	432	182	186	223	336	245	633	200	432	182	186	223	335	245	620	195	421	177	181	217	328	238	302	150	49.8
B2	615	192	417	175	178	213	325	234	628	198	428	180	183	220	332	242	612	191	415	174	177	212	323	233	296	148	50.2
Mean	613	191	415	174	177	212	324	232	625	196	424	178	182	218	330	239	607	188	410	172	175	209	320	229			
SD	15	7.2	13	6.1	6.3	8.6	8.7	9.9	7.5	4.0	6.6	3.4	3.5	4.8	4.5	5.5	12	5.7	9.9	4.8	5.0	6.8	6.9	7.8			
CV (%)	2.5	3.8	3.0	3.5	3.6	4.1	2.7	4.3	1.2	2.1	1.6	1.9	1.9	2.2	1.4	2.3	2.0	3.0	2.4	2.8	2.9	3.3	2.2	3.4			

EOM, exogenous organic matter; SRES, special report on emissions scenarios; GCM, general circulation climate model; SD, standard deviation; CV, coefficient of variation; CO, compost; BE, bioenergy by-products; AD, anaerobic digestates; MBM, meat and bone meals; AR, animal residues; CR, crop residues; AW, agro-industrial wastes; SW, sewage sludges.

SOC accumulation potential (31–40 t C ha^{-1}) are situated in: (i) the river Po valley, (ii) the coastal area of Emilia Romagna, Abruzzo, Marche and Apulia, (iii) the area between Apulia and Basilicata, (iv) the interior part of Tuscany, (v) central Sicily, and (vi) western part of Sardinia. SOC increments due to the repeated annual addition of meat and bone meal are reported on **Figure 6**. In comparison to compost addition, practically only the two lower classes of SOC increment (1–10, 11–20 t C ha^{-1}) are predicted by model simulation of SOC trends in meat and bone meal amended soil.

Figure 7 shows the simulated increase in SOC stocks considering compost addition only to arable soils, in order to simulate a more realistic scenario of compost application to the easier accessible plain areas. The arable land with higher sequestration potentials is located in the North-Western part of Italy.

Simulations performed by applying EOMs to either the land with the greatest or lowest C storage potential showed, in the case of compost, an average increase of SOC per unit area of 55.7 and 26.9 t C ha^{-1}, respectively (**Table 5**). In the case of meat and bone meal the simulated increases of SOC after 100 years of amendment were 18.9 and 7.2 t C ha^{-1}, respectively. Similar simulations were performed for the climate scenario GCM2 A1FI and the results for compost were 52.4 and 26.3 t C ha^{-1} and for meat and bone meal 16.5 and 6.8 t C ha^{-1} for the area with the greatest and lowest C sequestration potential, respectively (**Table 5**). The two climate scenarios were selected on the basis that they resulted in the largest (PCM B1) and smallest (GCM2 A1FI) C sequestration potential of added C (**Tables 3**, **4**). In general, the ratio between SOC accumulation in soil with the greatest and lowest C storage potential was at around 2.5 (**Table 5**).

Calculation of SOC stocks were performed at fixed soli depth. It is known that soils are characterized by a great variability in profile thickness and consequently conversion to a standard depth could affect the accuracy of prediction of total SOC stocks, especially in grassland use. However, we were mainly interested to assess the variability of the SOC increase due to EOM addition and this is not affected by soil depth. Considering that taking into account the actual soil depth would have required an increase in

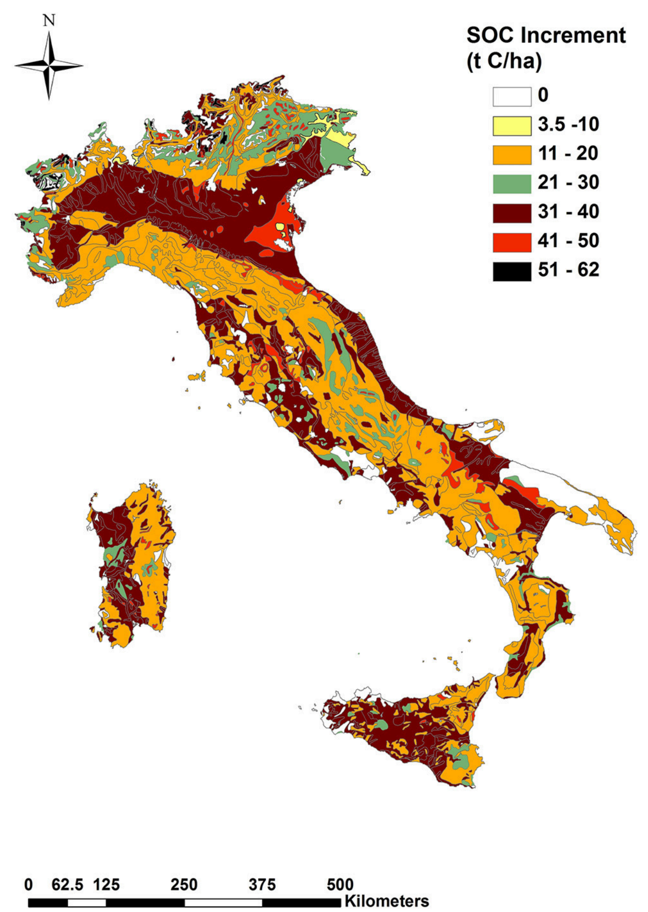

FIGURE 5 | Map of modeled increase in soil organic C (SOC, t ha^{-1}) after 100 years of compost addition (1.0 t C ha^{-1} y^{-1}) to all the Italian soils with agricultural land use (climate scenario PCM B1). The increase in SOC refers to the business as usual scenario in 2100.

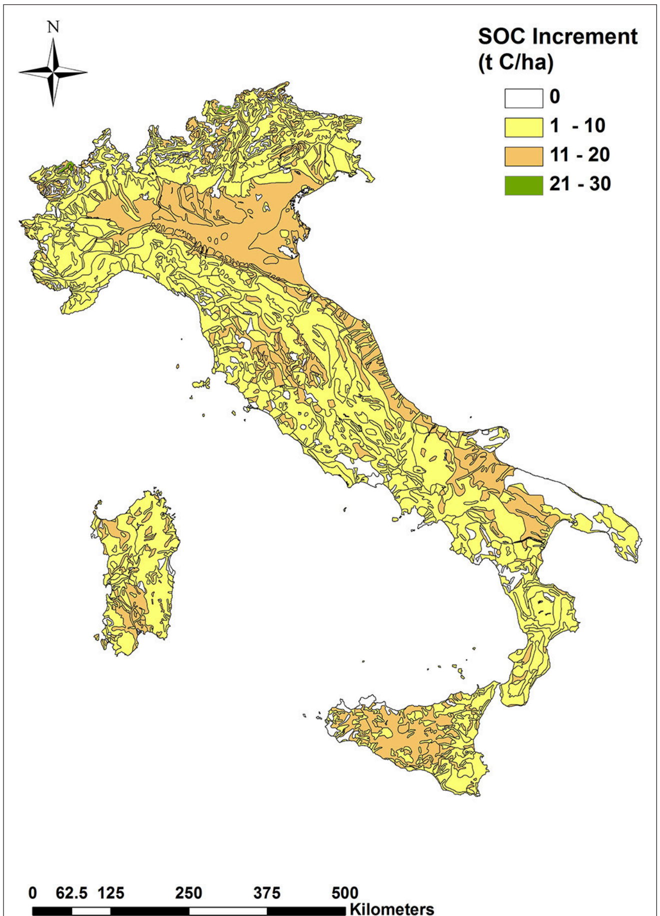

FIGURE 6 | Map of modeled increase in soil organic C (SOC, t ha^{-1}) after 100 years of meat and bone meal addition (1.0 t C ha^{-1} y^{-1}) to all the Italian soils with agricultural land use (climate scenario PCM B1). The increase in SOC refers to the business as usual scenario in 2100.

the complexity of the procedure, we chose to keep the procedure the simpler as possible compatible with the aim of the work.

Uncertainty

Figure 8 reports the uncertainty in C sequestration (expressed by the standard deviation bars) for the different EOM groups based on long term simulations considering default climate and soil data for the S. Martino soil and using the range of values for pool parameters derived from the optimization procedure of the modified model. The percent uncertainty with respect the mean soil C sequestration value for the different EOMs groups varied from 5.3 (agro-industrial wastes) to 38.4% (compost).

The uncertainty introduced by each specific pool parameter (calculated as percentage change in C sequestration at the average parameter value using the range of pool parameter from the optimization procedure) is depicted in **Figure 9**. Such uncertainty varies from 0 to 48.6%. In the case of EOM groups characterized by 3 EOM pools (CO, AD, and AW) the uncertainty is mainly attributable to the partition coefficients of EOM in the REOM and HEOM pool, while in the EOM groups presenting only two pools, uncertainty is almost entirely introduced by variability in the decomposition rate of resistant pool (K_{REOM}).

DISCUSSION

Sensitivity Analysis

To test the effect of the modifications carried out on the standard RothC model, a sensitivity analysis (SA) was performed to assess the effects of varying EOM model parameters on model outputs. This analysis allows the EOM parameters which have a major impact on the simulated C accumulation to be identified.

Results of SA for SB, characterized by two EOM pools, indicated K_{REOM} as the more sensitive parameter (**Figure 1**; **Table S1**). Such outcome is in agreement with findings of Stamati et al. (2013) who showed that total plant litter input and RPM decomposition rate constant were the RothC parameters with the highest sensitivity. This result confirms the importance that the stabilization degree of EOM exerts on the long term storage of added C. Moreover, it is also important to consider that the inverse relationship between K_{REOM} and C sequestration potential is not linear, as model output is more sensitive at smaller values of the parameter, i.e., little decreases in the decomposition rates results in a more than proportional increase in EOM-C storage (**Figure 1**).

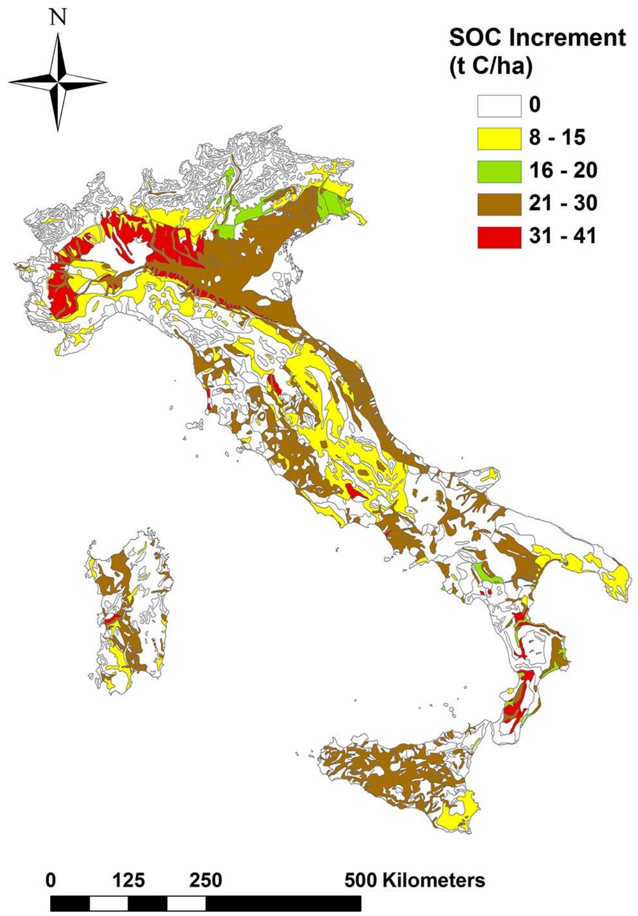

FIGURE 7 | Map of modeled increase in soil organic C (SOC, t ha^{-1}) after 100 years of compost addition (1.0 t C ha^{-1} y^{-1}) to Italian arable soils (climate scenario PCM B1). The increase in SOC refers to the business as usual scenario in 2100.

In the case of EOM characterized by 3 pools, typically the composted substrates, the most influential parameter on the model output were the f_{REOM}/f_{HEOM} and f_{DEOM}/f_{HEOM} ratio, especially at lower values (i.e., high contents of humic-like substances) (**Figure 2**; **Table S2**). This result was expected given the slow degradation rate of HEOM. For the same reason the model output is highly sensitive to variations in the f_{DEOM}/f_{HEOM} ratio especially at low values. These results underline the relevance that even small increases in the degree of stabilization may have on the long term conservation of added C.

Conversely to the case of EOM presenting 2 pools, model output was not very sensitive to the decomposition rate of REOM pool.

Generality Test

Generality, for the specific case of EOM amendment, implies the capacity of the model to simulate a large number of EOMs acceptably, rather than to predict excellently only few EOMs added to the soil (Petersen et al., 2005). This could be achieved by identifying a common set of EOM parameters for EOM groups characterized by organic materials with similar origin, treatment, and characteristics.This would extend the range of applicability of the model, because it would avoid the necessity to perform specific optimization for every EOM type.

The generality test showed that the difference in terms of SOC accumulation utilizing mean and specific pools parameter was reasonably low, being lower than 10% (**Table 1**). These results indicate that the range of SOC variability within each group is limited and therefore a common set of parameters for EOM group can be used to simulate SOC in soils amended with each of the EOM type belonging to the group with an acceptable level of confidence.

Long Term Modeling of Amended Soil

Potential C Sequestration and GHG Offsetting of Soil Amendment

Result of long term SOC simulations of amended soils showed that EOM quality exerts a significant impact on the amount of EOM-C that ultimately will remain in the soil (**Table 3**),

TABLE 5 | Modeled mean SOC increment (t ha^{-1}) after 100 years of soil amendment with different EOM type to the Italian agricultural soils (213,750 ha) with the highest and lowest potential for soil C sequestration.

Climate scenario	Land potential for SOC sequestration	EOM group								Average
		CO	BE	AD	MM	AR	CR	AW	SS	
		SOC increment (t ha^{-1})								
PCM B1	Land with largest SOC sequestration potential	55.7	22.0	42.4	18.9	19.5	25.8	30.5	29.4	30.5
	Land with smallest SOC sequestration potential	26.9	7.8	17.7	7.2	7.3	8.6	14.0	9.3	12.3
	Ratio	2.1	2.8	2.4	2.6	2.7	3.0	2.2	3.2	2.6
GCM2 A1FI	Land with largest SOC sequestration potential	52.4	18.9	38.4	16.5	17.0	21.9	28.1	24.9	27.3
	Land with smallest SOC sequestration potential	26.3	7.4	17.2	6.8	7.0	8.1	13.5	8.8	11.9
	Ratio	2.0	2.5	2.2	2.4	2.4	2.7	2.1	2.8	2.4

EOM, exogenous organic matter; PCM, GCM, general circulation climate models; B1, A1FI, emissions scenarios; CO, compost; BE, bioenergy by-products; AD, anaerobic digestates; MBM, meat and bone meals; AR, animal residues; CR, crop residues; AW, agro-industrial wastes; SW, sewage sludge.

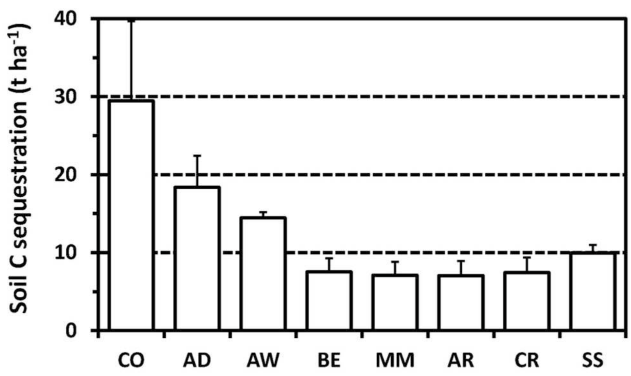

FIGURE 8 | Uncertainty in soil C sequestration for different EOM type added to the S. Martino soil at a rate of 1 t C ha y^{-1} for the period 2001–2100. CO, compost; BE, bioenergy by-products; AD, anaerobic digestates; MBM, meat and bone meals; AR, animal residues; CR, crop residues; AW, agro-industrial wastes; SW, sewage sludges. Error bars represent standard deviation of the different estimates of C sequestration using the range of pool parameters derived from the optimization procedure.

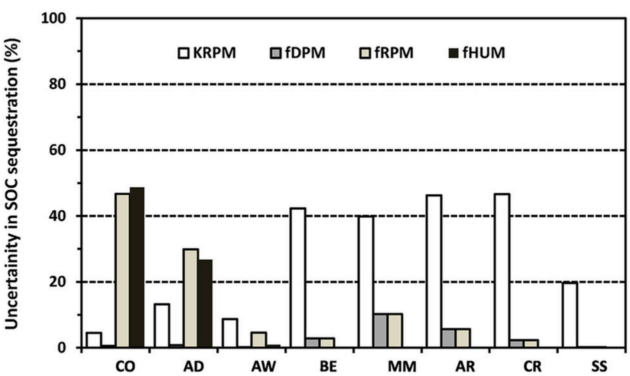

FIGURE 9 | Uncertainty in soil C sequestration introduced by the different EOM pool parameters describing EOM quality. CO, compost; BE, bioenergy by-products; AD, anaerobic digestates; MBM, meat and bone meals; AR, animal residues; CR, crop residues; AW, agro-industrial wastes; SW, sewage sludges. The uncertainty introduced by DPM was extremely low (<1.1%) and therefore not included in the graph.

as application of the same amount of C may result in a 3.5-fold difference in the potential for C sequestration. Compost and anaerobic digestates were the EOM groups for which the model runs anticipated the larger SOC accumulation. The potential of compost for soil C accumulation is widely recognized (Smith P. et al., 2005) and is mainly attributed to the presence of humic-like substances, whose extreme diversity and lack of regular polymeric structure impair efficient enzymatic degradation (De Nobili et al., 2001). In the case of anaerobic digestates the degradation of cellulose, soluble starch and glucose in the acidogenic phase of the anaerobic process leads to the formation of a partially stabilized residue. The potential of two-phase olive mill waste as a C source to promote C sequestration is well-recognized and mainly attributed to its high content of ligno-cellulosic substances (Sanchez-Monedero et al., 2008). Conversely, meat and bone meals, animal residues and bioenergy by-products were the EOMs less indicated to foster C sequestration. The potential yearly C sequestration rate per unit area found in the present study for compost (0.385 t C ha^{-1} y^{-1}) is similar to the values reported by Smith P. et al. (2005) for compost (0.4 t C ha^{-1} y^{-1}), Smith et al. (2008) for manure/biosolid application (0.42 t C ha^{-1} y^{-1}) and Freibauer et al. (2004) for amendment (0.40 t C ha^{-1} y^{-1}) in European soils, Yokozawa et al. (2010) for Japanese arable soils (0.30 t C ha^{-1} y^{-1}) and Minasny et al. (2017) for paddy soils in Asia (0.24–0.46 t C ha^{-1} yr^{-1}). The potential yearly C sequestration rate determined in the present study for Italian compost amended soil is markedly higher of that reported by Mondini et al. (2012) (0.13 t C ha^{-1} yr^{-1}). Nevertheless, such evaluation was performed utilizing the standard version of RothC, which considers organic matter entering in the soil to be composed only by decomposable and resistant material. These results suggest the inadequacy of the standard RothC model for the simulation of SOC in amended soil, because its structure does not allow the huge variability in the composition and properties of EOM to be taken into account. As a matter of fact, a sensitivity analysis performed by Falloon (2001) on the standard RothC showed that the model is relatively insensitive to variations in the quality of C inputs, as varying DPM/RPM ratio for plant inputs from 0.1 to 2.0 (i.e., 20-fold variation) resulted in a SOC decline from 29.0 to 24.3 t ha^{-1} (i.e., 16% variation). Conversely, the possibility to define specific partition coefficients and constant decomposition rates for EOM pools in the modified model caused variations in the SOC accumulation up to 1.8-fold: addition of 1 t C ha^{-1} y^{-1} of either CMC compost or blood meal to the same soil for 100 years resulted in SOC contents of 75.1 and 42.7 t ha^{-1}, respectively (**Table 1**).

The Carbo-PRO web-tool for simulation of C sequestration in amended soil developed by INRA and based on RothC (Carbo-PRO, 2012) gives a maximum yearly sequestration potential of 0.27 t C ha^{-1} y^{-1} for a yearly application of 1 t C ha^{-1} of compost with a good degree of stability for a period of 100 years. Model parameterization of the web-model was based on biochemical properties of EOM evaluated by the Van Soest method. Thuriès et al. (2002) suggest that in very stable compost part of the lignin pool can be transformed into soluble humic substances resistant to microbial degradation. Consequently, biochemical fractions based on the Van Soest method may lead to an overestimation of the labile fraction and an underestimation of the stable fraction, mainly responsible for the build up of SOC stocks.

Peltre et al. (2012) reported values of potential C sequestration in compost amended soil similar to those evaluated in the present study. However, such values were calculated considering a period of application of 20 years and it is well-known that the effectiveness of strategies such as compost application in building up SOC stocks tends to decrease after several decades, as the soil approaches saturation (Stockmann et al., 2013). The most stable compost in the study of Peltre et al. (2012) presented partition coefficients of 0.0, 0.8, and 0.2 for DEOM, REOM and HEOM, respectively. These values do not seem to properly reflect the nature of stable composts, considering that in mature composts lignin, assumed as a proxy for the resistant pool of EOM (Thuriès et al., 2002), ranges from about 30% up to 54% of organic matter (Sanchez-Monedero et al., 1999; Thuriès et al., 2002; Francou et al., 2008; Doublet et al., 2011).

The significant power correlation between net CO_2 cumulative emission and potential for C sequestration of each EOM group (**Figure 3**) suggests that the net C mineralization of residues during laboratory incubation is an indicator of their potential for C sequestration, but that such relationship is not linear. Results confirm the well-known importance of the degree of stability (as indicated by the rate of mineralization) in determining the long term potential of C sequestration of EOM added to the soil (Katterer et al., 2014). The power correlation between C mineralization and simulated C sequestration indicates how large increases in SOC accumulation could result from slight increases in the degree of stabilization of added EOM and suggests increased stabilization of organic amendments prior to soil application as an option to enhance C sequestration (Kirchmann and Bernal, 1997). In particular, the occurrence of a stable C pool (humic substances-like) greatly enhances the capacity of the residue to build up SOC stocks, as indicated by the results of the sensitivity analysis (**Figure 2**; **Table S2**).

Results of long term simulation, besides to highlight the importance of EOM quality, indicate the overall effect of the different pedoclimatic conditions in determining the variability in the potential to build up SOC stocks, as the combination of the different EOMs and pedoclimatic conditions resulted in a range of annual potential of C sequestration exceeding 1 order of magnitude. This evidence suggests spatial explicit SOC modeling as a key tool for the optimization of soil amendment at large scale (see section Spatially Explicit Modeling of SOC in Amended Soils).

The effect of the different climate scenarios on the C sequestration potential predicted by the model is consistent with the anticipated consequences of these scenarios on climate paeameters (**Table 2**). The relationship between climate parameters and SOC accumulation potential (**Figure 4**) could be explained on the basis that changes in T and ET predicted by all 12 climate scenarios were always positive, while in the case of precipitation contrasting estimates (i.e., positive and negative variations) were provided by the different climate scenarios (**Table 2**). Furthermore, it has to be considered that an adequate soil water content increases SOM decomposition, but in the presence of an optimal temperature, i.e., the effect of precipitation on SOM mineralization is best elucidated by considering the interaction of precipitation and temperature (Smith J. et al., 2005), as indicated by the significant relationship between potential SOC sequestration and ET (**Figure 4**).

The annual rate of GHG emissions for Italy in 2016 was estimated by the European Environment Agency (EEA-European Environment Agency, 2018) to be 117 Mt CO_2-C_{eq} y^{-1}. Therefore, the range of average annual potential of C sequestration in Italy in response to the application of EOM estimated in the present work (1.75–6.15 Mt C y^{-1}) only represents 1.5–5.3% of the total annual GHG emissions in Italy. It is also important to consider that the available EOM in Italy is not sufficient to cover all the suitable land. For instance, the estimated annual production of compost for 2020 in Italy is 1,800,000 t. At a rate of 1 t C ha^{-1}, this could be applied to 213,750 ha, representing about 1.66% of the total Italian agricultural land (12,885,186 ha). Considering the mean annual C sequestration rate of compost predicted by the simulation performed with the modified RothC (0.385 t C ha^{-1} y^{-1}; **Table 3**) the total C that can be sequestered every year in soil by compost amendment is about 82,300 t (corresponding to <0.1% of the annual rate of GHG emissions for Italy). This value is consistent with an amount of 98,200 t of C estimated by Arrouays et al. (2002) for France considering the actual compost production of France. Therefore, even in the non-realistic hypothesis to apply compost, which is one of the EOMs with larger potential for C sequestration, to all the Italian agricultural land, the contribution of soil amendment in tackling GHG emissions is limited. These results are in agreement with those of Smith (2004a) who concluded that C sequestration can play only a minor role in offsetting GHG emissions. However, it is important to consider that even if soil C sequestration by EOM application may have little benefit for climate change mitigation, the increase in SOC content is likely to have several beneficial and important impacts on soil quality and ecosystem functioning (Powlson et al., 2011).

Spatially Explicit Modeling of SOC in Amended Soils

Spatially explicit modeling of SOC in amended soils clearly showed the relevance of EOM properties in determining the amount of added C that will be stored in the soil, as in the case of addition of compost and meat and bone meal (**Figures 5**, **6**). Large scale SOC modeling also underlined that the characteristics of the agricultural land play an important role in determining the C storage potential of EOM (**Figures 5**, **7**). Spatially explicit modeling can be useful for the evaluation of the effects of site properties on EOM-C accumulation and in elucidating the role of the interactions between the different factors involved in determining future SOC stocks in amended soils.

A first important interaction is that between temperature and precipitation (**Figure 4**). It is largely acknowledged that there is a direct relationship between temperature and the rate of EOM decomposition due to the effect of temperature on both metabolic activity of soil organisms responsible for EOM decomposition and hydrolytic enzymatic activity (Franzluebbers, 2004). But also soil water content, which is influenced among others factors by precipitation, may affect the rate of EOM mineralization. The soil moisture content is not linearly correlated with decomposition, as suggested in the present work by the lack of correlation between precipitation and SOC accumulation, but affects the storage of added C when the soil water content is out of the optimal range for decomposition, generally considered to be between 10 and 50 kPa (or 30–60% water-filled pore space) (Franzluebbers, 2004). Low water contents may offset the effect of temperature on decomposition by reducing soil water films, which in turn inhibits extracellular enzyme activity and decreases substrate availability and microorganisms mobility (Franzluebbers, 2004; Davidson and Janssens, 2006). Leiros et al. (1999) demonstrated that the effect of a 2°C temperature increase on the rate of EOM decomposition is roughly counterbalanced by a simultaneous 10% decline in soil water content. On the other hand, also excessive soil moisture can decrease the rate of EOM mineralization due to limited O_2 availability into the soil (Gabriel and Kellman, 2011). Therefore, a better understanding of EOM decomposition can be achieved by considering the interaction of temperature and moisture. The relevance of the interaction between these two factors is illustrated in the present study by the significant correlation between ET and the potential for SOC sequestration (**Figure 4**), as ET reflects the effect of both temperature and soil moisture, with the latter being influenced by precipitation. The significant inverse relationship indicates that SOM mineralization is affected by temperature as long as soil moisture is within an optimal range for decomposition process. Furthermore, in the present research, while there is a general inverse relationship between SOC accumulation and temperature (**Figure 4**), there are also notable exceptions to this behavior, with soils presenting a high potential for C accumulation located in areas characterized by high temperatures, such as Southern Italy (**Figure 5**). However, these areas are characterized by low precipitation and the restriction exerted by low soil water content on EOM decomposition could explain why significant potential for C sequestration were also predicted for some of the hottest areas of Italy. The relevance of interaction between temperature and precipitation was also highlighted in previous studies. Smith J. et al. (2005) predicted faster SOC decomposition rates in areas where temperature increased, but at the same time, soil water moisture remained sufficiently high to enable mineralization. Likewise, Fantappiè et al. (2011) found that variations in SOC recorded in Italy between 1961 and 2008 were significantly affected by the interaction of temperature and precipitation. The importance of soil moisture as a key factor in regulating SOC mineralization has been emphasized by Fuentes et al. (2012) in a SOC simulation study performed for the 2007–2087 period in Northeastern Spain. The authors suggest that the simulated increase in SOC stocks in the studied area, characterized by prevailing semiarid conditions, is due to the effect of low soil moisture content on SOC decomposition, along with the likely increase in plant net primary production due to the rise in CO_2 content caused by climate change.

The combined impact of temperature and precipitation on EOM-C storage could also be seen in the SMU with the largest C accumulation potential that are all situated in the mountain region of Northern Italy (**Figure 5**), characterized by mean annual low temperatures and high precipitation. In these areas the climatic conditions are favorable to a slow down of the decomposition process by decreasing microbial activity and limiting O_2 availability. These results are in agreement with findings of Saby et al. (2008) and Lemenih and Itanna (2004), who demonstrated a trend in SOC that is directly proportional to the mean annual precipitation and inversely proportional to the mean annual temperature.

Another important interaction in determining EOM-C storage is between land use and climate. It is widely acknowledged that grassland promotes C sequestration with respect to arable soils, mainly due to avoided soil disturbance, larger input of plant residues and higher production of root biomass.

Goidts et al. (2009) accounted for Southern Belgium a mean SOC content of 36.4 and 92.2 t C ha^{-1} for cropland and grassland, respectively. In the present study, all the SMUs with the largest SOC increase (50–60 t C ha^{-1}, for compost amended soils) presented grassland as land use and low temperatures and large precipitation. It is generally acknowledged that evaluation of plant-derived C input in grassland soils is affected by a large degree of uncertainty and therefore this source of variability could affect the accuracy of predicted SOC for grassland systems. However, the effect of this uncertainty is relevant when considering SOC prediction in absolute terms, but has a lower impact when considering SOC in relative terms (i.e., difference between amended and not amended soil), as in the case of our work, because the same C input from plant residues were attributed for the amended and not amended soil. When considering the different SOC increase due to amendment this mainly reflects the interaction of EOM with pedoclimatic conditions (**Figures 5–7**). Therefore, the higher SOC increase per unit area recorded in grassland soils amended with compost could be mainly attributed to the fact that grasslands are situated in areas characterized by a combination of climatic conditions (low temperatures and large precipitation) favoring a low rate of EOM mineralization. Accordingly, Smit et al. (2008) found grassland productivity to be positively correlated with precipitation and negatively correlated with temperature.

Taking into account the limited potential production of EOM, it is clear that the studied scenario (EOM application to all agricultural land) does not reflect a realistic soil management option. However, the creation of a relation between spatial data and a dynamic soil C model represents a valuable tool for farmers, land managers, and policy makers for the optimization of the available resources. Simulations considering EOMs addition to all agricultural land, despite EOM scarcity, are significant as they enable obtaining a spatial representation of the potential of land for EOM C accumulation that can provide useful information for an effective management of EOMs. As an example, application of the estimated production of compost for 2020 to either the soil presenting the largest or the smallest C sequestration potential resulted in a 2.1-fold difference in SOC increase (climate scenario PCMB1) (**Table 5**). Spatially explicit modeling indicates the areas where the combination of climate, soil properties and land use results in the largest increase in SOC and therefore maps such as those reported in **Figures 5–7** can be useful for resource optimization by providing advice as to where EOM might be applied to obtain larger C sequestration.

The simulations performed on the land with contrasting capacity for C sequestration could also provide an indication on the relative importance in determining C accumulation of the different pedoclimatic conditions present at national level. Such results indicate that in soils amended with the same EOM, contrasting pedoclimatic conditions may cause a 2.5-fold differences in SOC accumulation (**Table 5**). These variations may be compared with those caused by the different EOM groups (3.5-fold difference, **Table 3**) and suggest that the quality of EOM added to the soil exerts a larger impact in determining SOC accumulation than variations in pedoclimatic conditions at national level.

Uncertainty of Long Term Modeling Due to the Different Quality of EOM

Regional modeling of amended soil under climate change is affected by different limitations and sources of uncertainty, but a quantification of all sources of uncertainty in the long term RothC prediction of C sequestration potential was beyond the scope of the present work. Limitations and sources of uncertainty related to simulations performed on unamended soils under climate change at regional scale will not be discussed here. A thorough evaluation of uncertainty of RothC following land use change was already performed by Stamati et al. (2013).

Given the aim of the present study, uncertainty analysis was focused on how the range of variability in EOM quality (i.e., partitioning factors and decomposition rates) is propagated along the model and it is translated into variability in the model output (Smith and Smith, 2007). Uncertainty analysis associated to the variability in EOMs was performed in a similar way to the sensitivity analysis. The main difference is that sensitivity analysis was aimed to test the behavior of the modified model, i.e., to determine how the model responds to variation in its components, while the purpose of uncertainty analysis was to determine how much variability is introduced into the model output due to the actual range of variation in the inputs. For this reasons input values during sensitivity analysis were changed arbitrarily using also unrealistic values, whereas input values in uncertainty tests were altered according to the range of variability of pool parameters determined during the optimization procedure.

The uncertainty in C sequestration for the different EOM groups (range 5.3–38.4%) was lower than the variability reported by Smith et al. (2014) for differently treated organic residues, as uncertainty in their work was always higher than 50%. The EOM group presenting the higher uncertainty is compost (**Figure 8**) and this can be attributed to the fact that the data set utilized for the analyses includes soil amended with compost with different degree of stabilization. The variability in the long term prediction of SOC trends at national scale under climate change associated to the different levels of EOM quality estimated in the present study is below the range of overall uncertainty in the model (65.6–70.8%) evaluated by Stamati et al. (2013) in a long term RothC simulation of C sequestration potential following conversion from cropland to set-aside.

The results concerning the evaluation of variability introduced by the different pool parameters indicate a clear difference between EOMs characterized by two or three EOM pools. In the first case the parameter showing the higher effect on C sequestration uncertainty is the decomposition rate of the resistant pool. In the latter case, uncertainty is mainly affected by the partition of the EOM between the resistant and humus pool (**Figure 9**).

The performed uncertainty analysis allows the model response to a broad range of EOMs (DeLonge et al., 2013) to be evaluated. Furthermore it provides an evaluation of the error on the estimate of SOC stocks, accounting for all possible variation in the models inputs regarding EOM quality (Wattenbach et al., 2007).

CONCLUSIONS

The main outputs of the study on the application of the modified RothC to the long term SOC modeling of amended soils at national (Italy) scale under climate change can be summarized as follows:

- EOMs greatly differ for their long term (100 years) soil C sequestration potential (range of annual rate of C sequestration: 0.110–0.385 t C ha^{-1} y^{-1}; 3.5-fold difference)
- the contribution of soil amendment in tackling GHG emissions is limited: soil C sequestration potential of compost applied for 100 years to all Italian agricultural land at a rate of 1 t C ha^{-1} y^{-1} (climate scenario PCM B1) was 6.15 Mt C ha^{-1} y^{-1} corresponding to 5.3% of total annual GHG emissions in Italy
- spatial explicit modeling of amended soil indicated a high variability in long term potential of SOC accumulation (1 order of magnitude) due to the combination of EOM type, environmental properties (soil, climate) and management options (land use and management)
- large scale spatial modeling of soil organic C can suggest ways to optimize resources by identifying the areas with the largest potential for EOM accumulation: 100 years of application of the whole compost produced in Italy to the land with the smallest and largest potential for C sequestration resulted in a mean SOC increment of 27 and 56 t C ha^{-1}, respectively (i.e., 2-fold increment)
- spatially explicit modeling of SOC in amended soils could be useful to highlight the relative importance of EOM quality and pedoclimatic conditions in the SOC evolution observed: in the present study the different EOM properties had a major impact than variability in pedoclimatic conditions in determining long term SOC accumulation

It has been underlined by several authors that there are considerable differences in the turnover rates and substrate utilization efficiencies of EOM between laboratory and field conditions. Consequently, the transfer of the optimized parameters resulting from laboratory studies to field sites has to be done with caution and the model based analysis of amended soil cannot be interpreted in terms of absolute values for certain sites and management practices. The reliability of the approach proposed in this study could only be validated by comparing the results of the simulation with data from long term experiments dealing with soil amendment with different EOMs. This step is essential to ensure the transferability to field conditions of the proposed procedure for the evaluation of soil C sequestration in amended soil and represents the main future development of the present work.

The relevance of this works is that it quantifies the relative differences of several types of EOM in their potential to build up SOC stocks at national scale under climate change and therefore can be useful to identify EOM properties, agricultural management options and environmental conditions more conducive to soil C retention of EOMs.

Model simulations indicate a wide range of variation in C sequestration potential as a consequence of long term amendment with contrasting EOMs. A reliable estimation of SOC accumulation by soil amendment at country-scale therefore requires that soil models should be capable to accommodate the huge variability in EOMs quality. Findings of this study highlight the importance of specific calibration and modification of existing soil C models for amended soils to enhance the reliability of soil C modeling to warranty the sustainability of agricultural ecosystems.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this manuscript will be made available by the authors, without undue reservation, to any qualified researcher.

AUTHOR CONTRIBUTIONS

CM linked the data set, performed the model runs, wrote the paper, and reviewed drafts of the paper. MC retrieved and organized the geographical soil database, prepared figures, and reviewed drafts of the paper. TS loaded and analyzed output of model runs into a GIS environment, prepared graphical displays in a spatial form, and reviewed drafts of the paper. FF retrieved and organized climate data and reviewed drafts of the paper. AG retrieved soil and land use data and reviewed drafts of the paper. M-SM prepared RothC input and setup files of soil, meteorology, and land use data, prepared the tables, and reviewed drafts of the paper.

FUNDING

This study was performed under the framework of the EU project FP7 KBBE.2011.1.2-02 FERTIPLUS "Reducing mineral fertilizers and agro-chemicals by recycling treated organic waste as compost and bio-char" (EC Grant Agreement n. 289853) co-funded by the European Commission, Directorate General for Research & Innovation, within the 7th Framework Programme of RTD, Theme 2 - Biotechnologies, Agriculture & Food. This publication reflects the author's views, findings and conclusions and the European Commission is not liable for any use that may be made of the information contained therein. MC is supported by a Ramón y Cajal research contract from the Spanish Ministry of Economy and Competitiveness.

ACKNOWLEDGMENTS

The authors would like to express their gratitude to Emanuela Vida for keen dedication and skilful work in performing the incubations experiments and the laboratory analysis. The authors are very deeply grateful to Kevin Coleman for information and explanations on the RothC model, for advice and suggestions on the modification of the model and for the development of the spatially explicit version of RothC.

This manuscript includes content that first appeared in the doctorate thesis of CM. This is the only form in which it has appeared, is in line with the author's university policy, and can be accessed online (Mondini, 2014).

SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenvs.2018.00144/full#supplementary-material

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Conflict of Interest Statement: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.