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Chapter 14

A Basic Concept on Modelling Soil Organic Carbon

Nimai Senapati, Subhadip Ghosh, Heiko Daniel and Amitava Rakshit

14.1 Introduction

Soil organic carbon (SOC) is a complex and mixture of diversified materials ranging from rapidly decomposable plant parts to microorganisms and make up a vital part of the soil. Enumeration of SOC dynamics is becoming more important as this can greatly impact soil productivity and sustainability. The amount of SOC is a balance between the build-up from inputs of new plants and animal materials and the constant losses, where the carbon (C) decomposes and the constituents separate to mineral nutrients and gases, or are washed or leached away. Positive build-up of SOC levels is possible when there is abundance of water, nutrients and sunlight, whereas continuous fallow favours SOC loss.

There are five principal pools which regulate the C cycle on earth—oceanic pool (~38,000 Pg, $\text{Pg} = 10^{12} \text{ kg} = 10^{15} \text{ g} = \text{Gt}$), followed by the geologic (~5,000 Pg), pedologic/soil (~2,500 Pg to one meter depth, organic and inorganic), atmospheric

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(~760 Pg) and biotic pool (~560 Pg) [1–2]. Soils contain about 1,500 Pg of organic carbon globally in top 1 m, which is roughly twice the amount of C in the atmosphere as carbon dioxide (CO₂) and about three times the amount of C in vegetation [1, 3–4]. Although the SOC pool is small compared with that of the oceans, potentially it is much more labile in the short term [1]. Using respective estimates of 1,500 and 720 Pg of C in soil and the atmosphere, and an atmospheric concentration of 390 ppm for CO₂, a 1% change in the amount of C stored in soils would equate approximately to an 8 ppm change in atmospheric CO₂ concentration, provided all other components of the C cycle remained constant [5]. Thus, small change in flow of C into or out of soil C pool could have dramatic impact on a global scale [6].

Diffusive process plays an important role in SOC dynamics through mass and gaseous movement and their transportation. The major factors controlling the size of the SOC pool and its movement are land use, land use change (LUC), climate, soil, management practice and technology [2, 6–8]. Agricultural soils are known to be C depleted due to tillage, disturbance, aeration and mineralization [9–10]. However, there is a considerable potential to sequester and store additional C by modifying soil management practices in such soils. Accurate quantification of inputs of C into and outputs of C from soil is essential to assess C sequestration potential and changes in SOC with time. Such measurements will help unravel the mechanisms that control C storage and formulation of robust models of soil C dynamics and turnover. Understanding the response of the soil C reserve and its transportation to change in different factors is of critical importance. The SOC turnover models are able to simulate SOC dynamics under various land uses (forest, grassland, cropland, etc.), management practices (crop rotation, ploughing, fertilizer application, irrigation, stubble management, soil amelioration, etc.), technological improvement (varietal improvement, better machinery, improved agronomic knowledge, etc.) and climatic conditions [8, 11–14]. Thus, they could help in investigation of change in SOC dynamics under different scenarios and may also help in refining our understanding of SOC turnover processes by pointing out our knowledge gap.

14.2 Soil Organic Carbon Models

A model is a simplified representation of reality, designed to meet different objectives [15]. A model may be a physical miniature of real entity, such as a clay sculpture, a hypothetical description of a complex entity or process, or a schematic/mathematical representation of a real-world system, theory, phenomenon, or situation.

SOC models represent turnover or decomposition of SOC as well as its transformation in soil–plant–atmosphere system. One of the earliest SOC models [16] to describe C accumulation or loss from soil was:

$$\frac{dx}{dt} = -kx + A,$$

where dx = change in state variable (e.g. soil C)

k = first order rate constant

A = addition rate (mass t^{-1}) which is independent of loss and the amount present

Since then many SOC models have been developed to meet different specific objectives.

14.3 Application of Soil Organic Carbon Models

The SOC turnover models are widely used in many disciplines—soil science, agronomy and environmental sciences. These models help to improve our understanding of C turnover process in soil as well as underlying C stabilization mechanisms in soil [13–14, 17]. At the same time, the models are now even being extensively used to extrapolate our understanding of SOC dynamics both temporally (future projections) [8, 12] and spatially, i.e. from national [18], regional [19] to global scales [20]. Another important application of SOC models is in agronomy, through its incorporation into decision support systems to improve agronomic efficiency and environmental quality, e.g. APSIM [21], DSSAT-CSM [22], SUNDIAL-FRS [23], etc.

The SOC models can be used to explore and investigate SOC dynamics under different management and environmental scenarios even beyond the realm of experimental work [8, 12]. They can be used for interpolation and extrapolation of experimental data both on time and space, and also making projections of SOC behaviour under current and future environmental and management conditions [14]. The SOC models are now increasingly being used by the policymakers also at the national, regional and global scales, for example, in post-Kyoto debate on capacity of terrestrial ecosystem to store C [24].

14.4 Classification of Soil Organic Carbon Models

SOC turn-over models are broadly classified as:

- a. Process-oriented models
- b. Organism-oriented/food-web model
- c. Cohort model

These models are described below.

14.4.1 *Process-Oriented Model*

Process-oriented models focus on the processes controlling the movement and transformation of matter or energy. Process-based models can be divided into:

- a. Single compartmental model where SOC models consider SOC as one homogeneous compartment. [16]
- b. Two compartmental models where SOC is considered as two compartments. [25]
- c. Multi-compartmental model considers SOC multi-compartmental, e.g. RothC [26], CENTURY [27], etc.

The first two types of SOC models are mostly static, where the environmental variables remain constant, whereas the models under type (c) are mostly dynamic, where the environmental variables vary with time.

Most of the SOC models are process-based multi-compartmental, describing SOC as a finite number of compartments or SOC pools, each of which is homogeneous, well mixed and characterized by its position in the model's structure and its decay rate [13–14, 28]. Decay rates are usually expressed by first-order kinetics with respect to the concentration (C) of the pool as:

$$\frac{dC}{dt} = -kC,$$

where t is the time, k is the rate constant of first-order kinetics. The pool's half-life ($h = (\ln 2)/k$), or its turnover time ($1/k$) is sometimes used instead of k to characterize a pool's dynamics.

With a lower decay rate constant, the stability of the organic pool is higher with higher half-life and turnover time. The compartments interact by exchanging materials, and by exchanges with the environment [29]. The flow of C within most models represent a sequence of C going from plant and animal debris to the microbial biomass, and then to soil organic pools of increasing stability. The output flow from an organic C pool is usually split into a microbial biomass pool, another C pool, and under aerobic condition into atmospheric CO_2 . Two parameters control the split flow, viz., microbial efficiency and stabilization/humification factor, which control the flow of decayed C to the biomass and humus pools, respectively. The sum of the efficiency and humification factors must be lower than one to account for the release of CO_2 [14].

Most of the present day's models are multi-compartmental process-based models. For example, out of the 33 models, currently available within the Global Change and Terrestrial Ecosystems (GCTE), and Soil Organic Matter Network (SOMNET) database [30], 30 are multi-compartmental process-based models.

14.4.2 Organism-Oriented/Food-Web Model

Organism-oriented models focus on flow of energy and matter (C and N) through food webs of soil organisms [31–32]. Such models are dynamic and explicitly account for different trophic levels or functional groups of soil biota. Food-web models require a detailed knowledge of the biology of the system to be simulated and are usually parameterized for application at specific sites.

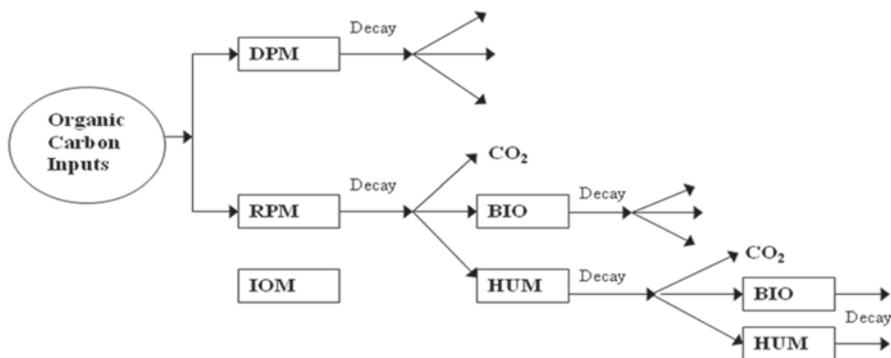


Fig. 14.1 Structure of the Rothamsted carbon model (*RothC*) (after [26]). *DPM* Decomposable plant material, *RPM* Resistant plant material, *IOM* Inert organic matter, *BIO* Microbial biomass, *HUM* Humified organic matter

14.4.3 Cohort Model

This type of model considers each fresh addition of plant debris as a separate cohort, which decays in a continuous way. These models describe decomposition as continuum. Most of such models are dynamic models and account SOC as one pool, which decays with a feedback loop into itself. The SOC pool is divided into an infinite number of components, characterized by its quality with respect to degradability as well as impact on the physiology of the decomposers. One of the examples of this type of model is Q-SOIL [33]. This model is quality dependent and is represented by a single rate equation which represents the dynamics of each SOC component. Exact solutions to the rate equations are obtained analytically [34].

Among the three types of models discussed, process-based multi-compartmental dynamic models are most popular due to (a) ease of use and transferability, (b) their successful coupling with GIS software, (c) their different internal parameters are easier to estimate and calibrate for specific purposes, and (d) they are easily scaled up. Different compartments actually simplify very complex physical, biological and chemical characteristics of SOC, and thus help to understand and depict the underlying turnover process [14]. Figures 14.1 and 14.2 show the structure of the two most popular process-based multi-compartmental models, viz., Rothamsted carbon model (RothC) [26] and CENTURY model [27]. A detailed overview on the SOC turnover models could be found elsewhere [13–14, 35].

14.5 Factors Affecting Turnover of Soil Organic Carbon in Models

Decomposition rate constants of different compartments or SOC pools follow the first-order kinetics and are constant for a given set of biotic and abiotic conditions. For nonoptimum environmental circumstances, the maximum value of rate constant

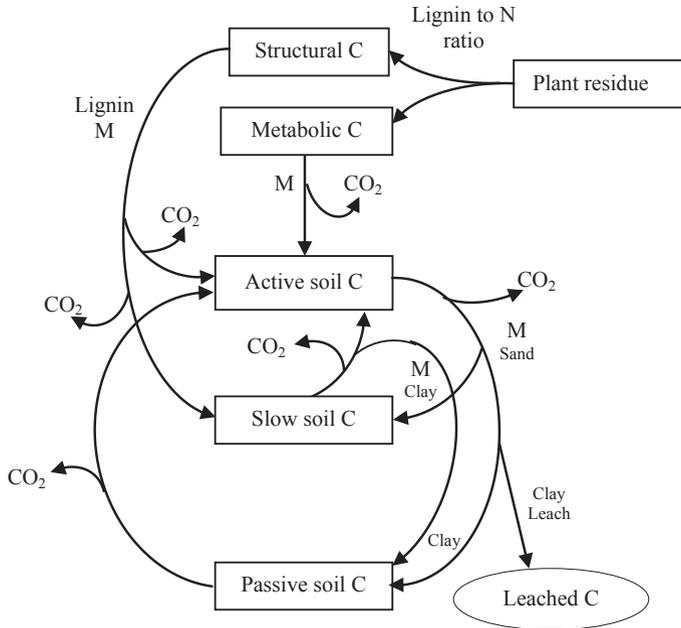


Fig. 14.2 A simple structural diagram of the SOC sub-model of the CENTURY model. (*M* : Multiplier for effect of moisture, temperature, cultivation, *Leach* : H₂O leached below 30 cm)

(*k*) is modified by multiplication with a reduction factor μ —ranging from 0 to 1. Environmental factors considered by SOC models for the modification of *k* include soil temperature, water, oxygen, pH, nitrogen, clay content, cation exchange capacity, salinity, type of vegetation, plant cover and tillage [13–14, 36].

14.6 Initialization of SOC Models

Model initialization, the initial distribution of total SOC between model pools, has been described as the most crucial part of a simulation study as it can influence the model prediction of soil C stock [37–38]. Incorrect or flawed initialization potentially leads to improper assessment of interannual variability, and can also produce fallacious trends in output as the state variables drift back towards the model ideal [38]. As various pools in SOC models are based on qualitative concepts and often do not correspond to measureable fractions [28, 39], the partition of SOC pools may lead to an initialization problem. Thus, the model may reflect not only the effect of the modelling objectives, but also the initialization procedure. The most common approach to solve the initialization problem is to achieve the initial SOC pool distribution by a spin-up run of the model, i.e. a run of the model over several hundreds to thousands of years to find equilibrium/steady state SOC, assuming initial SOC

and its distribution among the model pools are at equilibrium/steady state with the current land use and climatic conditions [8, 40]. The observed soils, however, may not be at equilibrium due to disturbances such as fire, erosion, land use and management changes [41]. The equilibrium/steady state assumption for the ecosystem C cycle has been challenged [42] and its limitation in modelling approaches emphasized [41].

In the second method, where recent land use and management condition is known, the model is started with default or steady-state pool distribution and then run for a few decades to obtain a quasi-steady state distribution under recent conditions [43]. However, there is rarely enough information about the past condition for a large area to initialize the model correctly. A third approach is to run most pools to steady state and then adjust the slowest pool so that the total SOC content matches the measured value [41]. Rapidly turnover pools reflect the current and recent state of the system, while slowly turnover pools reflect historical condition. Additionally, a fourth method is using the statistical model-data fusion technique to match pool distribution with observed C dynamics during the period of model simulation [38, 44]. Another method of initialization of SOC model is initializing model with measured SOC pools.

The use of measured SOC pools has the advantage over other initialization methods, as field measurements are independent of the model or any assumption, and information on previous land use and management history are not required [45]. Any process that is ignored in the model, but which could influence SOC dynamics, is also taken into account in SOC partitioning. Thus, measured fractions reflect better the real site-specific conditions under which SOC is accumulated [45–46]. Once the SOC pools are measured by a reliable fractionation method, model initialization issues can be solved and model performance can also be improved.

14.7 Measured SOC Fractions and Conceptual Modelled Pools

Soil organic matter represents a chemically and spatially heterogeneous mixture of organic materials that exist along a continuum of various stage of decomposition [47]. Thus, SOC cannot be separated easily into different pools, rather it exists as one continuous pool with almost infinite range of turnover times from minutes to millennia [48]. However, to simulate SOC dynamics successfully, most of the process-based SOC models divided SOC into multiple conceptual pools defined by their sizes and turnover times which are governed by first-order rate constants and modified by different climatic and edaphic factors [13–14, 28, 38]. A pool may be defined as a compartment containing material that is chemically indistinguishable and equally accessible to plants or to the soil microbial population [49]. A measured fraction represents a pool when it is unique (i.e. it should not represent only a portion of chemically and biologically indistinguishable material) as well as non-composite [39]. On the other hand, some other researchers [48] have given importance

to the mechanisms and process of SOC stabilization in measured fractions/pools and for modelling SOC dynamics.

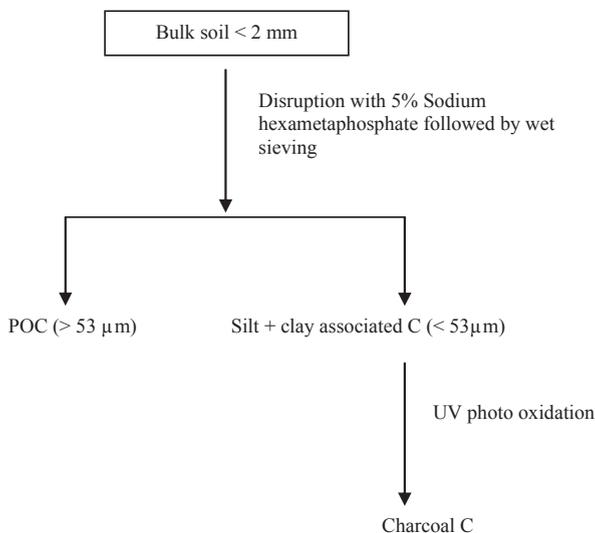
The SOC turnover in models has been described using simplified, deterministic, multi-compartmental simulation that is primarily based on empirically derived relationship. A major limitation of process-based multi-compartmental SOC models is that the various model compartments/pools are conceptual and often do not correspond to measureable fractions [39, 45, 50]. The only measured quantity is the microbial biomass and total SOC. Thus, it is often not possible to validate the dynamics of the modelled SOC pools with measured pools. However, measured pools in model have the advantage of thorough model evaluation and detailed initialization [39].

During the last few decades, different chemical methods were proposed to separate SOC into different pools [51–53]. The wet chemical fractionation methods consider the chemical nature of SOC as the only factor to influence the turnover rate of SOC pools, soil protection on SOC is ignored. Protected C is the influence of spatial arrangement of SOC in soil matrix (primary organo-mineral complex) and soil structure or aggregate (secondary organo-mineral complex) on stabilization/decomposition mechanism of SOC [50, 54]. Microorganism needs physical access of soil C in order to use it. In situations where the structure of a system does not control the accessibility of soil C to microbes (for example, forest litter layer), there chemical composition is the sole factor controlling soil C dynamics [50]. Soil microbes generally consume most organic substrate fallen or deposited onto the soil, yet there is accumulation of organic C in the soil. There must be some protection of incoming organic C in the way that prevents it from being completely consumed.

In the last few decades, physical fractionation methods have got the importance over chemical methods in fractionating SOC [55–57]. Although physical SOC fractionation methods elucidate spatial arrangement of primary and secondary organo-mineral complexes on SOC stabilization, they do not consider chemical or biochemical stabilization mechanisms, i.e. they are unable to give importance to chemical or biochemical nature or composition of SOC on its stabilization.

Therefore, to capture all the SOC stabilization mechanisms together, various approaches in SOC fractionation schemes have combined physical and chemical methods together subsequently. The most common approach is density or size fractionation prior to chemical analysis. By separating light fraction (LF) or the sand-sized fraction (particulate organic matter, POC), which contains mainly fresh plant material, through density fractionation or particle size fractionation, rest of the fractions are then further characterized chemically by acid hydrolysis or base extraction [58–61] or oxidation with $H_2O_2/NaOCl/Na_2S_2O_8$ [62]. There are some physicochemical methods which have shown good promise to relate measured SOC fractions with SOC pools. Skjemstad and others [63] have proposed a physicochemical method where they suggested partitioning SOC into POC (particle size fractionation), charcoal carbon (photo-oxidation) and humus (Fig. 14.3). Similarly, Zimmermann and others [45] suggested a physicochemical fractionation method to partition SOC into free LF/POC, dissolved organic carbon (DOC), stable aggregate and sand associated C (S + A), silt and clay associated C (s + c), and inert organic

Fig. 14.3 Physicochemical SOC fractionation method
POC particulate organic carbon, after [63])



carbon (rSOC) (NaOCl oxidation of silt + clay associated C) (Fig. 14.4). The concepts of relating these SOC fractions with model (RothC) conceptual pools are summarized in Figs. 14.5 and 14.6. Figures 14.3 and 14.5 show the partitioning of SOC into different fractions and relation of SOC fraction to SOC model (RothC) pools after [63]. POC is the measure of the resistant plant material pool (RPM), charcoal C is the measure of inert organic matter pool (IOM) and the quantity of humus pool (HUM) is calculated by $HUM = \text{total SOC} - (POC + \text{Charcoal carbon})$.

Similarly, Figs. 14.4 and 14.6 show the partitioning of SOC into different fractions and relation of SOC fraction to model pools after [45]. The measured C in rSOC fraction is directly associated with the IOM. The sum of C in POC and DOC fractions is split into decomposable plant material pool (DPM) and RPM using the ratio of DPM: RPM obtained by RothC model under equilibrium condition. The same procedure is also used to separate the sum of C in S + A fraction, and silt and clay fraction excluding rSOC fraction ($s + c - rSOC$) into biomass pool (BIO) and HUM.

One of the most important issues in the SOC model is inert organic matter pool (IOM). The issue of the IOM and its representation in models has been discussed [28]. IOM is defined in the model as an inert pool which does not undergo decomposition, means that it is not a dynamic pool. Although, different chemical methods are able to produce an old, chemically recalcitrant and stable SOC fraction, they nevertheless are not completely inert [64]. Further research for harmonizing measured IOM fraction of SOC and the IOM pool may be necessary.

Process-oriented multi-compartmental models could be improved by modifying different pools/compartments so that they are based on measurable SOC fractions which are unique, non-composite and in accordance with different SOC stabilization mechanisms

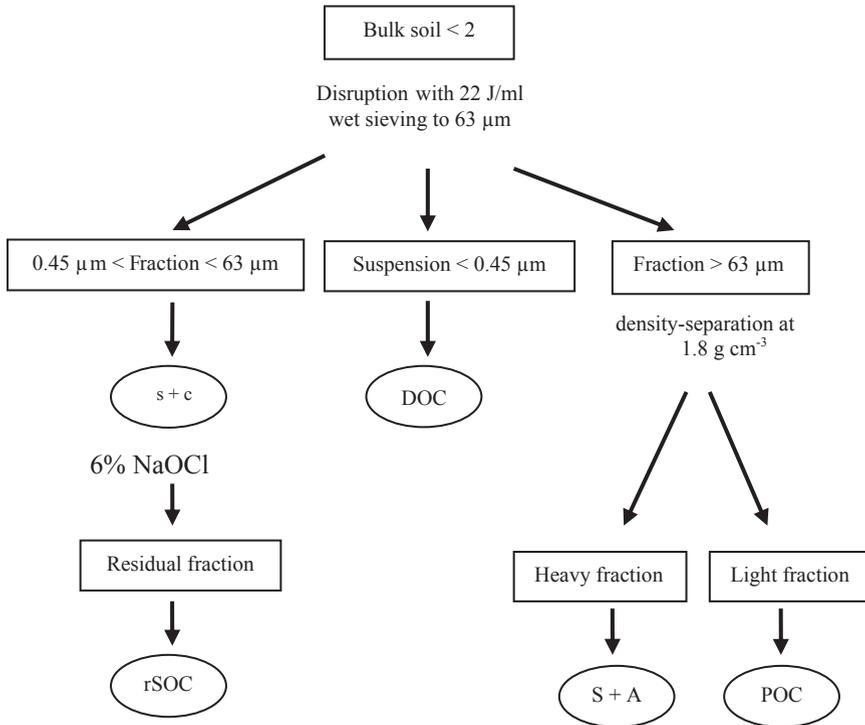


Fig. 14.4 Physicochemical SOC fractionation method. Particulate organic carbon (*POC*), Dissolved soil organic carbon (*DOC*), Soil organic carbon in sand and stable aggregate (*S + A*), Chemically resistant soil organic carbon/inert organic carbon (*rSOC*), Soil organic carbon in silt and clay fraction (*s + c*), after [45]

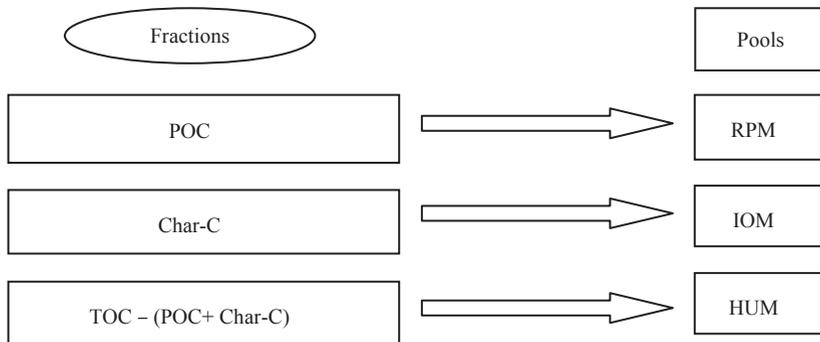


Fig. 14.5 The concept of relating measured soil organic carbon fractions to conceptual pools of RothC model *POC* particulate soil organic carbon, charcoal carbon (*Char-C*), total soil organic carbon (*TOC*), total soil organic carbon excluding *POC* and *Char-C* (*TOC (POC + Char-C)*), resistant plant material (*RPM*), inert organic matter (*IOM*) and humified organic matter (*HUM*), after [63]

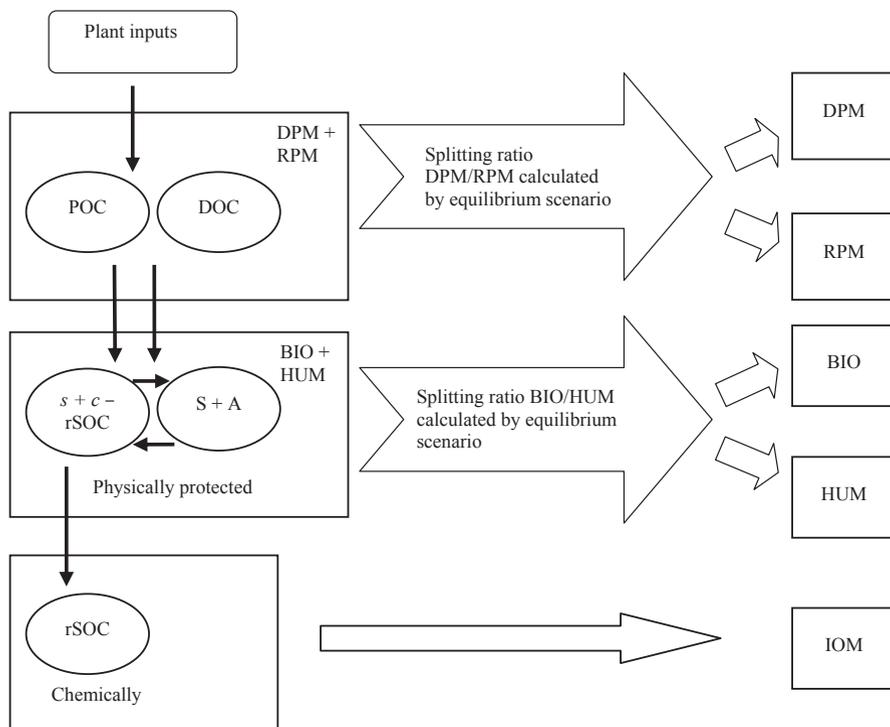


Fig. 14.6 The concept of relating measured soil organic carbon fractions to conceptual pools of RothC model particulate soil organic carbon (*POC*), dissolved soil organic carbon (*DOC*), soil organic carbon in sand and stable aggregate (*S + A*), soil organic carbon in silt and clay fraction excluding inert organic carbon (*s + c - rSOC*), chemically resistant soil organic carbon/inert organic carbon (*rSOC*), decomposable plant material (*DPM*), resistant plant material (*RPM*), microbial biomass (*BIO*), humified organic matter (*HUM*) and inert organic matter (*IOM*), oval represents fraction, square represents pool, after [45])

14.8 Black Carbon and Modelling Soil Organic Carbon

Black carbon (C) is an inorganic carbon compound produced from incomplete combustion of organic materials having a graphitic microstructure [65]. Black C is resistant to oxidation and microbial activity and so is persistent on a geological timescale [66]. Due to this recalcitrant nature, black C is assumed to represent part of the inert organic carbon pool. This pool is expected in higher proportion of total SOC in fire prone regions, for example at the continental scale, black C comprises 0–82% of the total SOC in Australia [67]. The importance of black C in the simulation of SOC was demonstrated [67] and the result showed a reduction in simulated CO₂ emissions by 18.3 and 24.4% in two Australian savannah regions in response to a warming of 3 °C over 100 years by including a realistic black C stocks in prediction models. Hence, quantification of the amount of black

C is important in SOC modelling. Historically, black C in soils has been calculated by digesting away organic matter using nitric acid and heat, and then sorting char particles by hand or under a microscope [68]. New analytical methods for estimating char materials in mineral soils include using benzenepolycarboxylic acids (BPDA) during nitric acid digestions as markers for black C [69], chemical digestion [70] and using a combination of high energy ultraviolet photooxidation and nuclear magnetic resonance spectroscopy [71] or a combination of chemical oxidation followed by solid-state ^{13}C nuclear magnetic resonance spectroscopy [72]. Schmidt and others [73] tested several forms of thermal oxidation, chemical oxidation, photo-oxidation, and a molecular marker method on Australian soils. The resulting black C values for individual sample varied over two orders of magnitude indicating great disparity between individual methods. One of the possible explanations for the wide range of the result is the different operational definitions of black C and clear cut boundaries of the different methods, which were developed for specific research questions.

14.9 Evaluation of SOC Models

Model evaluation is the prerequisite for model application and helps in the assessment of model performance [15]. The benefits of model evaluation are: (a) it shows how well a model can be expected to perform in a given situation, i.e. it determines the accuracy of the simulation, (b) it analyses the behaviour of model, whether the model responds in the expected way to the change in the conditions of simulation, (c) it determines which components of the model are most important in influencing the results, and (d) it can help in improving the understanding of the system as well as the model [13–15].

A graphical analysis gives a quick approximate evaluation, whereas a quantitative analysis determines the statistical accuracy of the simulation. Some statistics measure association (e.g. sample correlation coefficient) and others measure coincidence (root mean square error, relative error, mean difference, modelling efficiency, lack of fit, etc.) between the measured and simulated values. A higher association indicates similar trends between the measured and simulated values, whereas a higher coincidence indicates close proximity of the simulated values with the corresponding measured values. Figure 14.7 shows different model performances with different coincidences and associations between the measured and simulated values. A sensitivity analysis evaluates the behaviour of the model, whereas uncertainty analysis determines how much uncertainty is introduced in model output by each component of the model. All these model evaluation methods/parameters are defined and summarized in the literature [11, 15, 74].

Model performances are generally assessed using a long-term experimental data set. Models can be evaluated at different levels, viz., individual process level, subset process level (e.g. net mineralization), or the model's overall outputs (e.g. changes

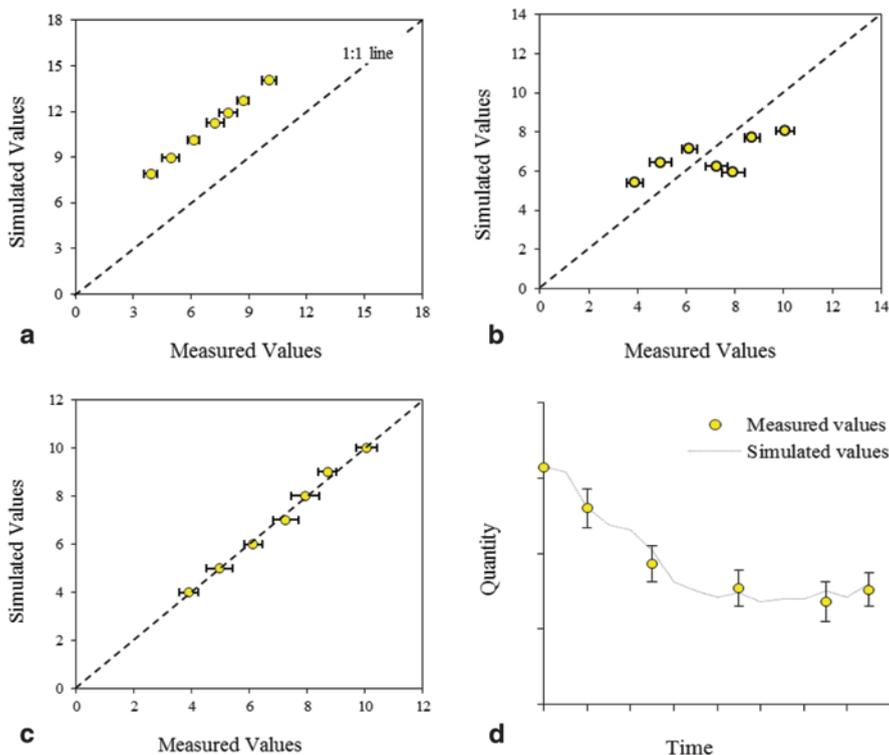


Fig. 14.7 An illustration of different hypothetical model performances with different coincidences and associations between measured and simulated values. **a** Higher association but lower coincidence, bad model performance. **b** Lower association but higher coincidence, bad model performance. **c** Higher association and coincidence, good model performance. **d** Higher association and coincidence in time scale, good model performance

in total soil organic matter (SOM) over time). Most comprehensive model evaluation to date has been done by Smith and others [11] with nine models using 12 data sets from seven long-term experiments covering arable lands, managed-unmanaged grasslands, and woodlands across the world.

14.9.1 Evaluation of SOC Models Under Land Use Change

LUC is a global concern and has adverse effects on the climate through emission of greenhouse gases [75]. Historically, soils have lost between 40–90 Pg C globally through cultivation and disturbance [76], and it is estimated that change in land use alone emitted 1.6 ± 0.8 Pg C yr^{-1} to the atmosphere during the 1990s [4, 77]. Expansion of the cropland is one of the major drivers of LUC and is likely to continue in

the future. The magnitude of changes of SOC following LUC vary widely among sites due to differences in environmental conditions (such as soil type, texture, mineralogy, etc.), climate, ecosystem productivity, plant species, and the management practices [7]. The prediction of changes in SOC as a consequence of rapid changes in land use is an important task for the future, and SOC dynamic models are one of the most promising tools in this respect.

Model performances are generally evaluated using the long-term field experimental data set, collected in chronosequence [11]. Model performance in simulation of changes in SOC under LUC can also be assessed using chronosequence data sets [78]. However, there are extremely few cases where chronosequence data have been collected before and after a LUC. In this respect, paired-sites offer an opportunity to study LUC effects on SOC and can provide a basis for SOM model evaluation. Paired-site consists of two sites, viz., a site where LUC already occurred several years before and an adjacent remnant, native-vegetation site, located on a common soil type, landscape position, and slope angle.

14.10 Projection of Soil Organic Carbon Under Climate Change

A number of studies have examined the potential of soil C sequestration for climate mitigation options [2, 4]; whereas, climate change will be a key driver of change in soil C stock during the twenty-first century [8]. Increases in mean air temperature are likely to accelerate SOC decomposition and loss of SOC in the future, if soil moisture is not a limiting factor [8, 12]. On the other hand, any increase in soil C input from, for example, increased ecosystem productivity through CO₂ fertilization or climate change, or technological and management improvement, could compensate the loss [8]. Increase in extreme climatic events and decrease in rainfall could reduce ecosystem productivity and thus could offset any positive impacts of climate change and CO₂ fertilization on soil C inputs through ecosystem productivity. Ultimately increase in SOC decomposition and changes in soil C inputs will determine the fate of soil C reserve under future climatic changes. Therefore, simulation of the fate of SOC under climatic changes is very important. There are some recent studies on projection of SOC under climatic changes across arable, forests and grasslands [8, 12, 46].

Grassland is one of the most important and widespread terrestrial ecosystems, covering approximately 40% of the global land surface, and containing the largest share (39%) of terrestrial soil C stocks (~580 Gt C) [79]. Any change in the SOC storage in grasslands will have a significant and long-term effect on global C cycles [80]. Hence, estimates of changes in grassland soil C stocks under climatic changes are of critical importance. A loss of 6–10% of the European grassland SOC stocks over 90 years (1990–2080) was projected by Smith and others [8] depending on the emission scenarios, whereas Xu and others [46] reported a loss of 2–6% of grassland SOC stocks in Ireland across different emission scenarios over 40 years

(2021–2060). Similarly, Senapati and others [81] estimated a loss of grassland SOC by 10–11 % due to the direct effect of climatic changes in Australia.

14.11 Limitation/Weakness/Scope of Improvement of the SOC Model

Soil microbial biomass is often represented as an active pool in SOC turnover models and thus remains a black box in terms of functionality [82]. Models often do not include the simulation of feedback of soil microbial biomass resulting from changes of a range of management practices [32]. Although there is no evidence of limiting SOC turnover by soil biota abundance, inclusion of the dynamics of soil biota explicitly and their feedback in the SOC models could improve model performance [83].

Soil protection towards SOC through aggregation is well known [60]. Disruption of soil aggregates is associated with loss of SOC, whereas generation of soil aggregates provides more retention of SOC. However, most of the models do not count the whole process of soil aggregate formation and destruction, and hence ignore soil structure dynamics and its implication on SOC stabilization or decomposition [48]. Inclusion of soil aggregate dynamics in the model might help in model improvement. Although there are some efforts to include soil aggregation factor in model [17], but still feedback between soil structure and microbial activity needs to be improved in the SOC turnover models.

Although the diffusive process plays an important role in movement and transportation of solutes and gaseous substances in SOC dynamics, SOC models often do not simulate the diffusive process explicitly. Further, model development regarding the role of diffusive process in SOC dynamics could be important.

Models often simulate inadequately the dynamics of different macronutrients (N, P, K), and other micronutrients especially their toxicity (e.g. Al toxicity), if any in the soil, along with the SOC dynamics. The SOC models generally simulate faster SOC turnover than reality in acidic soil, as the decomposition rate is up to two-thirds slower under acidic condition [43]. While some models account soil pH in turnover process of SOC, others do not. Adequate simulation of these factors together with soil C in the SOC turnover model could improve model overall performance. SOC models also need better integration with landscape as well as whole ecosystem processes.

14.12 Summary

The SOC turnover models are important tools for investigating the behaviour of SOC under current and future management practices, land use, LUC and climatic condition. The SOC models are now increasingly being used to assist policy

decisions at the national and international levels regarding future guidelines of land use, climate change and management practices. They are the important components of different agronomic decision support systems for improving agronomic efficiency and environmental quality. These models are useful in exploration, extrapolation, interpolation and explanation of experimental data. The SOC models are also important means of improving our understanding of C turnover process as well as underlying C stabilization mechanisms in soil.

Process-based multi-compartmental models are most popular and widely used SOC turnover models compared with other SOC models due to ease of use across different scales in space and time. Different compartments/pools actually simplify very complex physical, biological and chemical characteristics of SOC, and thus help in better understanding the SOC dynamics. However, various pools in multi-compartmental models are conceptual, based on empirically derived relationships and qualitative concepts, and often do not correspond to measurable fractions. Measured SOC fractions need to be unique as well as non-composite to represent a pool in the model. Although a combination of physical fractionation methods with chemical fractionation methods has the potential to relate measured SOC fractions to model pools, its applicability needs to be tested further.

However, the process-oriented multi-compartmental models could be improved by modifying their different pools/compartments so that they are based on measurable SOC fractions which are unique, non-composite, and in accordance with different SOC stabilization mechanisms. Once measured, the different SOC pools can be helpful in initialization of model explicitly. The use of measured SOC pools has the advantage over other initialization methods as the field measurements are independent of the model assumptions. Measured fractions reflect better the real site specific conditions under which SOC is accumulated; information on previous land use and management history are not required.

Model evaluation is a prerequisite for model application and helps in the assessment of model performance. Model evaluation provides confidence and reliability in the modelling. Different SOC models need to be evaluated comprehensively using reliable dataset as widely as possible before their use in a new environment other than their original environment, where they were developed. Model performances are generally evaluated using long-term field experimental data set, collected in chronosequence. In the absence of long-term chronosequence data sets, particularly under the scenario of LUC, paired-sites data sets could offer an opportunity for the evaluation of SOC models.

Climatic change is a key driver of change in soil C dynamics during the twenty-first century. Increases in mean air temperature are likely to accelerate SOC decomposition and loss of SOC in the future, if soil moisture is not a limiting factor. Increases in mean air temperature and CO₂ fertilization could increase ecosystem productivity, whereas increase in extreme climatic events and decrease in rainfall could reduce the same. Hence, projection of the fate of SOC dynamics under climatic change is very important. Reliable measures of black C in the fire-prone regions are very important in projection studies, as it influences the simulation of SOC dynamics.

The SOC models often simulate the dynamics of different macro- and micronutrients along with SOC dynamics inadequately. They also often do not account for soil pH explicitly, and do not simulate the whole process of soil aggregation and the dynamics of soil biota adequately. Inclusion of all these process/factors/parameters in the SOC models could represent the complex real life systems in a better way; it might improve the overall model performance.

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