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Review

Quantitative Approaches in Assessing Soil Organic Matter Dynamics for Sustainable Management

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Abstract: The aim of this study was to provide an overview of the approaches and methods used to assess the dynamics of soil organic matter (SOM). This included identifying relevant processes that describe and estimate SOM decomposition, lability, and humification for the purpose of sustainable management. Various existing techniques and models for the qualitative and quantitative assessment of SOM were evaluated to gain a better understanding of advances in organic matter transformation. This evaluation aimed to identify the strengths, limitations, and applications of these techniques and models, and to highlight new research directions in the field. Quantitative analysis of SOM can be performed using various parameters, including oxidation kinetics, lability, carbon management index, humification degree, humification index, and humification ratio. On the other hand, qualitative evaluation of SOM can involve techniques such as oxidizability, high-performance size-exclusion chromatography, electrospray ionization Fourier transform ion cyclotron resonance mass spectrometry, visual examination, smell, assessment of microorganism content, plant growth, cation exchange capacity, type of organic material, and decomposition. These techniques and parameters provide valuable insights into the characteristics and transformation of SOM, enabling a comprehensive understanding of its dynamics. Evaluating SOM dynamics is of utmost importance as it is a determining factor for soil health, fertility, organic matter stability, and sustainability. Therefore, developing SOM models and other assessment techniques based on soil properties, environmental factors, and management practices can serve as a tool for sustainable management. Long-term or extensive short-term experimental data should be used for modeling to obtain reliable results, especially for quantitative SOM transformation analysis, and changes in the quality and quantity of SOM should be considered when developing sustainable soil management strategies.

Keywords: humification; lability; modeling; quantitative approaches; soil organic matter dynamics; sustainable management

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1. Introduction

Importance and Overview of the Advances in Evaluating Soil Organic Matter

Soil organic matter plays a vital role in maintaining and improving soil health and fertility [1–3]. It is also recognized as a key component for sustainable agriculture, contributing to soil productivity, agroecosystem functioning, and climate stability [4–6]. Higher levels of SOM are associated with improved water management, soil aggregate stability, hydraulic conductivity, ease of processing, rapid warming, nutrient retention, and increased productivity [7]. These benefits would be compromised without SOM [8–10]. Additionally, the quantity of organic carbon in the soil has implications for carbon sequestration and its impact on climate change [11]. Hence, it is recommended to apply and maintain organic fertilizers for SOM enhancement. However, their effectiveness depends on factors like quantity, quality, and environmental conditions [12,13]. It is important to consider the regulating mechanisms between soil, plants, and the environment, as excessive SOM accumulation is unlikely. Different agricultural practices have varying effects on SOM dynamics, with conventional methods accelerating decomposition and practices like reduced tillage, crop rotations, cover crops, mulching, intercropping, and balanced fertilization enhancing SOM pools [14]. Global research highlights the influence of land use, land type, and management practices on the change in resource quality, productivity, and stability [15–20]. One of the many reasons put forward to explain this dynamicity is the depletion or reduction in the quantity and/or quality of soil organic matter [14]. To explore and estimate these effects of organic matter dynamics, it is important to develop techniques, models, and indicators that would accurately describe the cause–effect relationship, the impact on the whole ecosystem, and the potential remedial actions.

Early SOM quantitative and qualitative evaluation studies included analyzing substances extracted from the soil [21–23] and measuring carbon dioxide fluxes at the soil and plant interaction level [24,25]. Later, studies on SOM dynamics were developed using improved physical, chemical, biological, spectroscopic, and thermal approaches [26–36]. Assessment of the soil organic carbon stocks at the global level and mathematical modeling were then introduced [37–39]. Several advanced analytical and simulation models are developed today to better understand SOM decomposition and transformation, including well-known models such as those developed by Stéphane Hénin in the 1940s and Parnas in the 1970s [40–42]. These models were first based on simple exponential decomposition functions and, later, on complex functions with concentration-dependent rates of decomposition [41,43–45]. Most analytical models have historically considered soil organic matter as a single homogeneous pool that decomposes with varying relative rates of decomposition over time. However, advancements in knowledge about computers, modeling, and simulations [46,47] have led to the development of different simulation models. It was not until the 1970s that Hanna Parnas first used a simulation model to describe SOM decomposition, which considered SOM as a heterogeneous mixture of different pools that decompose at varying relative rates over time [42]. Since then, various models with simple regression equations and complex designs have been developed to study and quantify SOM transformation [48–50]. To model and study the decomposition, lability, stability, and humification rate of the soil organic matter pool, different kinetics equations are used, including zero-order, first-order, and Michaelis–Menten equations. Zero-order kinetics describes the soil organic matter decomposition reaction as independent of substrate concentration and proceeds at a constant rate over time. It is expressed as

$$\frac{dC}{dt} = -k_0, \tag{1}$$

where dC/dt is the rate of change of soil organic matter (substrate) concentration and k_0 is the rate constant. First-order kinetics describes the soil organic matter decomposition reaction as substrate-concentration-dependent, and the rate varies according to changes in substrate concentration, temperature, and time. This is expressed as

$$\frac{dC}{dt} = -k_1 C, \tag{2}$$

where C is the substrate concentration and k_1 is the relative rate constant. Michaelis–Menten kinetics describes the soil organic matter decomposition reaction as dependent on the size and activity of the microbial biomass involved in substrate decomposition. The rate of decomposition is expressed as

$$\frac{dC}{dt} = -(\left(\frac{dC}{dt}\right)_{max} \times \frac{C}{K_c + C}), \tag{3}$$

where $(dC/dt)_{(max)}$ is the maximum rate of substrate decomposition, Kc is the half-saturation concentration, and C is the substrate concentration [28,51–55].

For sustainable SOM management, two categories of factors affecting the balance of SOM—natural and anthropogenic—need to be considered. Natural factors, such as climate, soil parent material, biota, and topography, regulate the input, output, and rates of decomposition of organic matter [56–62]. Anthropogenic practices that affect SOM balance include those that reduce SOM, such as the reduction in biomass production, organic matter input, and increased rates of decomposition and mineralization. These practices include conventional tillage, overgrazing, crop residue removal, and burning practices. Practices that increase SOM are those that increase biomass production and organic matter input, and decrease decomposition rates, such as balanced fertilization, cover crops, agroforestry, afforestation, regenerative agriculture, and pastoral practices [5,63–65]. Contrary to certain practices like conventional farming, sustainable regenerative activities support and maintain soil biological processes, increase biomass production, and help build soil organic matter. It is important to focus on reducing the rate of organic matter decomposition and increasing the input of organic matter by managing crop residues, using animals and green manures, avoiding burning, and adopting minimal soil disturbance practices [5,66–68].

Early indicators proposed to monitor the changes and transformation of organic matter include the carbon pool index (CPI), lability (L), lability index (LI), carbon management index (CMI) [69], carbon stock change [70,71], humification index (HI), humification degree (HD), humification rate (HR), oxidizability, soil cation exchange capacity, infrared and fluorescence spectroscopy, nuclear magnetic resonance, and visual examination [54,72–77].

The objective of this study was to identify and review relevant models, processes, approaches, and methods used for the quantitative evaluation of soil organic matter dynamics in different land use/land cover for effective management. Although few studies have addressed and assessed the advances in the modeling of soil organic matter transformations and its effects, this study provides a comprehensive overview of the current state of knowledge in this field and proposes further research directions.

2. Conceptualization and Terminology

Soil organic matter is a heterogeneous mixture of macro- and micro-organisms and living and non-living organic molecules from animal and plants at various stages of transformation [14,78]. The living fraction is relatively small and consists of plant roots and soil organisms, while the non-living fraction is more significant and includes light fractions primarily derived from plants and humus. Humus is composed of humic substances (humic acids, fulvic acids, and humins) and non-humic substances (carbohydrates, lipids, proteins, lignin, alkyls, and more) [79,80]. The functional pools of SOM differ in their levels of decomposition and can be classified as labile or stable fractions [13,32,68]. The labile fraction, also known as the active fraction, is light, a source of energy, and a substrate for soil micro-organisms. Importantly, it determines the soil's fertility regime. In contrast, the stable fraction is resistant to oxidation and decomposition and determines the long-term carbon stocks in the soil [16,81]. The stable fraction results from the degradation of biopolymers of organic materials in the soil and the progressive accumulation of more hydrophobic and recalcitrant molecules. Since the physicochemical properties and changing behavior of these fractions are not easily distinguishable, SOM is described according to its pools' decomposition and resistance instead of their chemical characteristics. The most commonly used terms for describing and studying organic matter are summarized in Table 1 [14,16,70,71].

Table 1. Terminology and description.

Terminology	Description
Litter	Organic material onto the soil surface excluding mineral residues.
Microbial biomass	The organic matter that is from the dead or cells of living microbial organisms.
Primary soil organic matter	Soil organic elements that are (or are not) partly decomposed and have not humified yet, comprising dead roots, other plant parts, and soil organisms. They consist of less stable fractions to biodegradability, they are highly oxidizable, and their cation exchange capacity is negligible.
Labile SOM	Actively decomposing free fractions of SOM.
Free SOM	Labile fractions of SOM with a high rate of decomposition.
Free light fraction SOM	Free SOM density fractionation gives free light fraction SOM and then occluded SOM fractions. The free light fraction is that from the organic matter of the outer surface of soil aggregates or pseudo-aggregates. They are more labile than occluded fractions.
Occluded SOM	The organic matter trapped inside aggregates is fractionated, resulting from ultrasonic disintegration of soil stable aggregates, leaving out heavy fractions or organominerals. They are more stable and their conversion time may range from decades to centuries. They are degradable once out of aggregates.
Organomineral SOM fractions	The SOM found in minerals form organomineral complexes. They are more stable and their conversion time may range from decades to centuries.
Particulate organic matter	Organic material corresponding to particle sizes of 53–2000 μm (Detritus, Litter of plants . . .)
Stable SOM	Resistant, passive, inert fractions of SOM to decomposition
Humus	Humified soil organic elements with stable fractions to biodegradation and oxidation or hydrolysis and with high cation exchange capacity. They remain in the soil after macro-organic matter and dissolved organic matter are removed. They are amorphous colloidal particles less than 53 μm.
Non-humic biomolecules	They are biopolymers including polysaccharides and sugars, proteins and amino acids, fats, waxes, other lipids, and lignin.
Humin	Insoluble part of organic matter after extraction of aqueous base soluble part. Alkaline-solution-insoluble organic material.
Humic Acid	Alkaline-solution-soluble organic materials, which precipitate on acidification of the alkaline extracts.
Fulvic Acid	Organic materials that are both soluble in alkaline solution and acidic solution of the alkaline extracts
Dissolved organic matter	Organic compounds that are soluble in water. They are less than 0.45 μm and are mostly found in soil solution
Resistant or Inert organic matter	They are organic materials with very long chains of carbon (heavily carbonized). They are materials of high carbon content like charcoal, charred plant materials, graphite, and coal and have a very long turnover time
Organic matter	Biomaterial under different levels of decomposition or decaying process.
Organic matter fractions	Measurable organic matter components.
Organic matter pool (stock)	Theoretically separated, kinetically delineated components of soil organic matter.
Carbon turnover	The average time taken for carbon mineralization and transformation in terrestrial ecosystem from one pool to another
Decomposition and transformation	Physical breakdown and chemical transformation of complex organic substrate into simpler components molecules.
Humification	Process of humic substances' formation from organic materials.
SOM modeling	Process of using mathematical models to analyze and simulate the changes of organic matter in the soil.

3. Overview of Measurement Techniques for Soil Organic Matter Assessment

Parameters that determine SOM status, soil health, and functions are generally difficult to measure directly. Therefore, they are evaluated by deriving indicators that correlate with soil conditions. Soil condition indicators may be chemical, physical, or biological, and can be either descriptive or quantitative. Descriptive indicators are qualitative and are used in the field, while quantitative indicators are assessed by laboratory analytical procedures [79,82]. Because total soil organic matter is often not sensitive enough to small and short-term changes due to its complexity levels and background, some studies have recommended using soil organic matter fractions (sub-pools) as more sensitive indicators to detect even small changes over a short period of time [19,69]. These fractions or sub-pools have been classified by various researchers based on their formation, levels, and ease of decomposition. They include labile, less-stable, and stable fractions. The most labile fraction can decompose in less than a year or two, while the actively decomposing fraction, including partially stabilized organic material from plants and microbial metabolites, may have a turnover of up to 26 years. There is also a chemically stabilized and resistant fraction with a radiocarbon age of up to 2500 years [28,83–85].

3.1. SOM Fractionation

Soil organic matter can be physically, chemically, and biologically fractionated to help in better understanding its composition, properties, and functions in soil [79]. Physical fractionation involves separating SOM based on its particle size, where smaller particles usually have higher decomposition rates and contain more labile SOM fractions. One of the commonly used physical fractionation methods is density fractionation, which separates SOM into different fractions based on their densities using a heavy liquid (e.g., sodium polytungstate) [86–88]. Chemical fractionation separates SOM based on its chemical properties, where different fractions are at different degrees of decomposition, stability, and reactivity. The most common chemical fractionation method is the acid hydrolysis or oxidation method, which separates SOM into different fractions based on their oxidation or solubility in acid solutions of varying strengths [32,52,56,82]. Biological fractionation separates SOM based on its microbial accessibility, where different fractions have different microbial decomposability and utilization. One of the commonly used biological fractionation methods is the substrate-induced respiration (SIR) method, which measures the microbial respiration rate of SOM fractions incubated with a specific substrate (e.g., glucose). This method measures fungal, bacterial, and total microbial contributions to glucose-induced respiration and the potentially active microbial biomass on decaying plant residues of differing composition [89].

3.2. Quantitative Techniques for SOM Measurement

Quantitative soil organic matter measurement techniques can be broadly classified into two categories, dry combustion methods and wet oxidation methods [90]. Dry combustion methods include thermal exchange, loss on ignition (LOI), and Walkley–Black (WB) methods. These techniques rely on the complete combustion of soil samples to determine the organic carbon content. Thermal exchange involves heating a soil sample in a furnace under an inert atmosphere and measuring the evolved CO_2. The LOI method involves heating a soil sample to a high temperature to burn off organic matter, and measuring the weight loss. The WB method involves adding a dichromate-sulfuric acid reagent to a soil sample, which oxidizes the organic matter and releases CO_2, which is then measured [91,92].

Wet oxidation methods involve the oxidation of dissolved organic material with dissolved oxygen at high temperatures. A strong oxidizing agent is used to release carbon dioxide or to change the absorbance properties of the soil sample. Wet oxidation methods include wet digestion and near-infrared reflectance (NIR) [93]. Digestion methods breakdown soil samples using acid (such as hydrochloric acid and hydrogen peroxide) digestion to release soil organic matter, while the NIR is a non-destructive method that uses the interaction of infrared light with organic matter to estimate the quantity and quality of organic matter by measuring using a spectrophotometer the reflectance or absorbance of near-infrared light by the soil sample. The choice between dry and wet methods depends on the accuracy and precision needed, time, resources, and all organic matter properties needing to be measured [75,94].

3.3. Qualitative Techniques for SOM Measurement

Qualitative techniques used to assess SOM are descriptive and involve visual examination. These techniques entail assessing physical properties of the soil such as color, texture, and structure [95–97]. A positive correlation has been observed between soils with high organic matter content and darker color, crumbly texture, and granular structure. Additionally, the smell test can be employed to identify organic matter, as soils with high organic matter content often have a rich, earthy smell. The number of earthworms, the soil crumb test, infiltration rate, plant growth, organic matter color, and crop residue decomposition can all serve as qualitative indicators of soil organic matter quality. Although cation exchange capacity (CEC) can also be used, other factors such as soil texture, pH, and mineral content can influence its accuracy [16,54,98–101].

Other important qualitative techniques include using infrared spectroscopy where infrared (IR) radiation identifies and quantifies functional groups in SOM. It can provide information on the composition and structure of soil organic matter as it measures the absorption and transmission of infrared light by soil organic matter functional groups, providing information on SOM quality, quantity, and composition. IR spectra can be collected from bulk soil samples, or from specific SOM fractions obtained by soil fractionation [102]. Fluorescence spectroscopy is another technique that uses the fluorescence properties of soil organic matter to characterize its composition and structure. It can provide information on the humification degree, aromaticity, and molecular weight of soil organic matter. It measures the emission of light from soil organic matter after excitation with ultraviolet or visible light. Fluorescence spectra are sensitive to SOM quality and can be used to assess changes in SOM quantity and quality due to management practices or environmental factors [103,104]. Pyrolysis mass spectroscopy (PyMS) is a technique that uses high temperatures to decompose soil organic matter into smaller fragments, which are then analyzed using mass spectrometry. It measures the mass and abundance of pyrolysis products generated from SOM upon heating to high temperatures in the absence of oxygen. PyMS provides information on SOM functional groups and the distribution of carbon and nitrogen within SOM molecules [105]. Nuclear magnetic resonance (NMR) is a technique that uses magnetic fields to analyze the structure and composition of soil organic matter. It can provide information on the molecular structure, functional groups, and chemical bonding of soil organic matter. It measures the relaxation times of nuclei within SOM molecules in response to a magnetic field [77]. High-performance size-exclusion chromatography is another technique that separates soil organic matter into fractions based on their size and chemical composition. It can provide information on the molecular weight, size distribution, and chemical composition of soil [106]. Electrospray ionization Fourier transform ion cyclotron resonance mass spectrometry (ESI-FTICR-MS) is a technique that measures the mass-to-charge ratios of SOM molecules. It combines electrospray ionization with Fourier transform ion cyclotron resonance mass spectrometry. It informs us about the molecular weight, elemental composition, and functional group composition of individual organic molecules, which helps in processes that control the SOM dynamics [107,108]. Likewise, it should be noted that the use of both quantitative and qualitative methods is often advised for a more comprehensive assessment of soil health and organic matter content.

3.4. Lability and Stability of Organic Matter in Soils

SOM is a fraction of soil composed of a heterogeneous mixture of plants and macro- and micro-organisms at different stages of decomposition. Their quality, quantity, and decomposition are essential for soil health, nutrients, and carbon cycling. Therefore, understanding the relationships between SOM fractions (labile fraction, stable fractions, and total carbon stock) can help to express the relative degree of lability, stability, and humification of overall soil organic matter, hence carbon management index development. It should also be added that variations in these sub-pools have been used in developing and understanding SOM dynamics models [14,16,19,103]. The constant supply of organic matter carbon depends on the available stock and estimated turnover speed. Hence, quantitative assessment of soil organic matter dynamics and its lability and stability could be monitored early using parameters such as carbon pool index (CPI), lability (L), lability index (LI), carbon management index (CMI) [69], carbon stock [70,71], humification index (HI), humification degree (HD), and humification rate (HR) [59,63,104] to be able to manage the available SOM changes.

$$\text{Carbon stock } = \frac{\text{TOC} \times \text{Ds} \times \text{e}}{10} \tag{4}$$

$$\text{CPI} = \frac{\text{TC in sample}}{\text{TC in reference}} \tag{5}$$

$$\text{L} = \frac{\text{Labile carbon (oxidized)}}{\text{Non} - \text{labile carbon(non} - \text{oxidized)}} \tag{6}$$

$$\text{LI} = \frac{\text{Lability in sample}}{\text{Lability in reference}} \tag{7}$$

$$\text{CMI} = \text{CPI} \times \text{LI} \times 100 \tag{8}$$

where TOC is total organic carbon, TC is total carbon, Ds is soil bulk density (g. cm^{-3}), e is the thickness of the layer (cm), CPI is carbon pool index, L is lability, LI is lability index, CMI is carbon management index.

$$\text{HI} = \frac{\text{NH}}{\text{H}} \tag{9}$$

$$\text{HD} = \frac{\text{H}}{\text{TC}} \times 100 \tag{10}$$

$$\text{HR} = \frac{\text{H}}{\text{TOC}} \times 100 \tag{11}$$

where HI is humification index, HD is humification degree, HR is humification ratio, NH is non-humified (labile) fraction, H is humified (Humic acid + Fulvic acid = non-labile) fraction, TOC is total organic carbon, and TC is total extracted carbon.

4. Modeling as a Tool for Sustainable Soil Organic Matter Assessment and Management

Soil organic matter models are mathematical representations that describe the dynamics of organic matter in soils over time. These models can be used to analyze or simulate the effects of management practices, climate change, and other environmental factors on available SOM, turnover rates, and other related soil properties (Table 2). SOM models are typically based on empirical or mechanistic approaches that help in predicting the future SOM trends [30,105,106]. The development and advancement in soil organic matter modeling from simple exponential decay functions, more complex functions with substrate concentration and time-dependent relative decomposition rate, and simple regression equations to more complex processes-based models have been a success in understanding and designing sustainable soils, SOM, crops, and climate management practices [23,47,75,104,107]. The progress in mathematical, computer, and simulation skills has allowed the development of different SOM analytical and simulation models and, as the measurement of the impact of a given management practice to SOM changes requires long-term or extensive short-term data, it is the same for modeling data for reliable results [41–43,50]. In this part, the most used analytical and simulation soil organic matter models are described and discussed according to their targets, importance, shortcomings, methodologies/theories, and quantitative elucidation. It concentrates on different models describing the evolution of organic matter in soils on the scale of several years or many short time scales, although there exist some others not discussed but that have almost the same characteristics as what is included in this study [49,75,108,109].

It should be noted that simulation models may be divided into two categories, comprehensive and summary models. Comprehensive simulation models are detailed models that attempt to simulate every process and variable involved in SOM dynamics, including plant growth, nutrient cycling, and microbial activity. These models can be complex and require a significant amount of data to run. They are designed for research purposes, their essential elements are thoroughly understood, and the available knowledge is incorporated. On the other hand, summary simulation models are simplified models that use a small number of key variables to predict SOM dynamics. These models are generally easier to use and require less data than comprehensive models. They are formulated with less detail and they are more suitable for applicative and predictive purposes. Comprehensive models are typically more accurate but require more data and computational power, while summary models are simpler and easier to use but may not capture all of the complexity of SOM dynamics [82,109].

Moreover, SOM models can be either mono or multi-compartmental and the choice among them depends on the objectives of the study, the amount and quality of available data, and the complexity of the system being modeled. Mono-compartmental models assume that all organic matter in the soil is equivalent and represented by a single pool, with a single set of parameters describing its decomposition and turnover. This type of model is simple to use and requires less data and fewer parameters, making it suitable for studies with limited data or when there is a need for rapid simulations. The mono-compartmental organic matter pool is considered as a single entity with a characteristic relative decomposition rate (k), which is either constant or changes with time. Multi-compartmental models, on the other hand, recognize that organic matter in the soil is composed of different fractions, each with distinct properties and turnover rates. These models represent different compartments; their decomposition and turnover are modeled separately, with parameters that describe the properties of each fraction. The existing and the added materials are partitioned into a number of pools, each with its own specific rate constant. This type of model is more complex and requires more data and parameters, making it more suitable for detailed studies that aim to capture the complexity of SOM dynamics [82].

4.1. Analytical Models

Soil organic matter analytical models are based on mathematical equations and formulas (such as calculus or linear algebra) that describe the changes in SOM over time. These models use assumptions and simplifications to predict SOM dynamics based on a few input parameters. They can provide rapid and efficient estimates of SOM dynamics, but their accuracy can be limited by the simplifying assumptions made during model development. Analytical models predict the dynamics of a system in certain conditions and make accurate predictions if the underlying assumptions are met. Generally, they are also easier to use and interpret than simulation models [82,110].

4.1.1. Hénin and Dupuis's Model

Around 1945, different corners of the world witnessed a radical modification of the farming systems where farming was oriented almost exclusively toward crop production, while that of livestock and therefore manure was almost completely disappearing. From that time, Stephane Hénin and his colleagues started developing a mathematical model that would assess a very complex process of soil organic matter dynamics by using simple basic assumptions, and undoubtedly, this represents one of the first attempts at mathematical modeling of soil organic matter dynamics. This is a single pool model that describes, with a one-year time, the evolution of soil organic matter whose changes are assumed to be homogeneous. This model assumes that for soil organic matter to remain constant over a given time, the output or destroyed (decomposed and mineralized) fraction has to be compensated for by the input or formed (humified) fraction [111]. Stephane Hénin supposed that more organic matter is destroyed per unit of time when its concentration in the soil is higher. The quantitative expression of this is

$$\frac{dC}{dt} = -kC \text{ or } C = C_0 \cdot e^{-kt} \tag{12}$$

where C is the content of not-yet-decomposed SOM at time t, in tons; C_0 is the total organic matter at t = 0, in tons; k is the relative decomposition rate; and t is time, in years.

Because the organic matter, A, which is formed from plant residues (and chemosynthesis) and incorporated into the soil, is assumed to be constant per unit time (year), this constant fraction of soil organic material is transformed into humus and was called the isohumic coefficient by Hénin [41]. The quantitative expression then becomes:

$$\frac{dC}{dt} = -kC + A \text{ or } C = C_0 \cdot e^{-kt} + A \tag{13}$$

where A is the annual input of organic matter (in tons).

Also, taking into account the humified fraction and mineralized fraction of organic matter [112], the quantitative expression would be presented like

$$C = C_0 \cdot e^{-k_2 t} + k_1 \cdot A \cdot \left(1 - e^{-k_2 t}\right) / k_2 \tag{14}$$

where C is the content of not-yet-decomposed (or humified) SOM at time t, in tons; C_0 is the total organic matter at t = 0, in tons; t is time (years); A is the annual input of organic matter, in tons; k_1 is the isohumic coefficient and depends on the nature of the inputs (organic material); and k_2 is the mineralization coefficient, depending on the pedo-climatic conditions [113].

4.1.2. Hénin et al.'s Model

Due to complications in distinguishing between stable humified and non-humified labile fractions of SOM, and as their proportions may largely depend on the procedure used, some authors have proposed using the term organic matter to represent both fractions, or all organic material found in soil at any time. However, it is important to note that these fractions are different [39]. A new two-component model was then developed to distinguish the labile fraction of organic matter from the stable humified organic matter fraction. This model assumes that labile organic matter is found in the light-density fraction, whereas stable humified organic matter is related to the high-density fraction [40]. The quantitative equations representing these two fractions are as follows: the free or light fraction is considered as fresh organic matter, while the stable fraction is considered as humus.

For the labile fraction,

$$\frac{dL}{dt} = A - \alpha L \text{ or } L = \left(L_0 - \frac{A}{\alpha}\right) \cdot e^{-\alpha t} + \frac{A}{\alpha} \tag{15}$$

where L is the labile organic matter (free or light) at time t, L_0 is the labile organic matter (free or light) at time t = 0, A is the annual input of organic matter, α is the decomposition (humification and mineralization) parameter, and t is time.

For the stable (humified) fraction,

$$\frac{dS}{dt} = k\alpha L - \beta S \text{ or } S = \left(s_0 - \frac{kA}{\beta}\right) \cdot e^{-\beta t} + k\left(L_0 - \frac{A}{\alpha}\right)\frac{\alpha}{\alpha - \beta}\left(e^{-\beta t} - e^{-\alpha t}\right) + \frac{kA}{\beta}\Bigg) \tag{16}$$

where S is stable organic matter or humus at time t; S_0 is stable organic matter or humus at time t = 0; k is the isohumic coefficient; β is a parameter of decomposition and mineralization of the stable (humified) fraction of soil organic matter; t is time; A represents the amount of labile (fresh) organic matter at any given time; L represents the total amount of labile organic matter at any given time; k is the rate constant for the conversion of labile organic matter to stable humified organic matter; α and β are rate constants for the decomposition of the labile and stable fractions, respectively; and L_0 is the total amount of labile organic matter at time zero.

4.1.3. Kortleven's Model

In 1963, Kortleven modified the previous model of Hénin and Dupuis to develop a new one based on quantitatively analyzed data, which helps understand the relationship between supplied humus, humus content, and productivity. In an experiment comparing fallowing and conventional management practices, he found that from a supply of crude organic matter, a certain constant part becomes humus each year, and from humus in soils, a certain constant part is mineralized each year. Thus, two constants have to represent the organic matter transformation: k_1 for the rate of humification and k_2 for the rate of mineralization [45]. With an equal organic matter supply per unit time (year), this would be represented as

$$H = \mathrm{H_m} - (\mathrm{H_m} - \mathrm{H_0})\ (1 - \mathrm{K_2})^t \text{ With } H_m = \left(\frac{k_1}{k_2}\right) A \quad (17)$$

where H is the humus content, $\mathrm{H_m}$ is the humus content at equilibrium with a constant supply of organic matter, $\mathrm{H_0}$ is the initial humus content, $\mathrm{K_2}$ is the rate of mineralization, t is the time in years, $\mathrm{K_1}$ is the coefficient of humification, and A is the raw organic material supply.

4.1.4. Kolenbrander's Model

In 1969, Kolenbrander proposed a mono-component model for mineralization of common organic material under agricultural conditions with a relative decomposition rate decreasing with time [114].

$$\frac{\mathrm{Y_t}}{\mathrm{Y_0}} = e^{-(n+(\frac{p}{t+1})\cdot t)} \text{ And } K = n + \left(\frac{p}{t+1}\right) \quad (18)$$

where p and n (no dimension over time) are empirical constant parameters specific for the organic material, and k is the average relative mineralization rate during the period between times 0 and t.

4.1.5. Godshalk's Model (1977)

Godshalk [115] adopted the models of Saunders [116] and the one developed by Bunnell [117] after Minderman [118] to develop his new one based on the biological and environmental influence on the decomposition process in lentic ecosystems, focusing on the rate and fate of products (components) of decomposition. The effects of plant species, temperature, and oxygen on the transformation of senescing macrophyte tissues were monitored.

Bunnell et al.'s model developed after Minderman is

$$\frac{\mathrm{dW}}{\mathrm{dt}} = \sum\nolimits_{\mathrm{i}=1}^{\mathrm{n}} -\mathrm{KiWi} \quad (19)$$

$$\text{The Saunders, (1972) model is : } \frac{\mathrm{dW}}{\mathrm{dt}} = -\mathrm{cWE} \quad (20)$$

$$\text{The Godshalk model is : } \frac{dW}{dt} = -a(e^{-bt})W \tag{21}$$

where W is the remaining organic material at time t; t is the time; E is the effective absolute enzyme concentration; W_i is the proportion of organic material i remaining at time t; K_i is the decay constant of organic matter i; n is the number of organic matter components; and a, b, and c are the decaying constants.

4.1.6. Jansen's Model

In 1984, Jansen used Kolenbrander's data and equation to develop the new model where the relative rate of mineralization is dependent on initial age and a temperature correlation factor [119,120].

$$K = 2.82\ (a + f{\cdot}t)^{-1.6} \tag{22}$$

$$Y_t = Y_0 * \mathrm{Exp}(4.7 \times (\mathrm{age} + f{\cdot}t)^{-0.6} - \mathrm{age}^{-0.6}) \tag{23}$$

$$f = 2^{(T-9)/9} \tag{24}$$

where Y_t is the quantity of remaining organic material at time t (years), Y_0 is the initial quantity of the organic material, k is the relative rate of mineralization (decomposition) at time t, age is the initial age (resistance to mineralization), f is the temperature correlation factor, and T is the temperature in degree Celsius.

4.1.7. Yin's Model

In 1994, Yin proposed an ecological model about litter production, decomposition, and accumulation in grassland ecosystems. The characteristics of litter long-term dynamics in grassland ecosystems were assessed as a function of input and output rate [121]:

$$\frac{dX(t)}{dt} = g(t) - k(t){\cdot}X(t) \tag{25}$$

where t is time, X(t) is litter biomass, g(t) is production rate, and k(t) is decomposition rate.

4.1.8. Andrén and Kätterer's Model (ICBM)

In 1997, answering to questions related to whether a given system is losing or sequestering soil carbon, what would happen to soil carbon with an increase in temperature (5 °C), what would be the effect of doubling the annual carbon input to soil carbon stocks, and what might be the reasons of uneven soil carbon in different regions, a two-component model was developed, comprising young and old soil carbon, two decay constants, and parameters for litter input, humification, and external influences. It was called the introductory carbon balance model [122].

$$\frac{dY}{dt} = i - k_1\ Yr\ \text{And} \tag{26}$$

$$\frac{dO}{dt} = hk_1\ Yr - Ok_2\ r \tag{27}$$

where Y is young pool soil carbon; O is old pool soil carbon; i is the mean annual soil carbon input; k_1 and k_2 are relative decomposition rates for young and old soil carbon pools, respectively; h is the humification coefficient, and r represents climatic (edaphic) factors.

4.1.9. Andriulo et al.'s Model

In 1999,Andriulo et al. [123] modified the Hénin and Dupuis model to develop a three-compartment model. This model consists of separating the organic matter into a stable and an active fraction, each with a specific mineralization rate. The stable fraction is assumed to be biologically inert or degrades extremely slowly, whereas the active fraction has a high rate of decomposition. On top of active and stable fractions, they also consider the initial carbon content to make three compartments. They found that the stable fraction of organic matter represents 2/3 of the initial stock: $C_s = \frac{2}{3}C_0$ [123,124].

$$C = C_s + C_{A0} \cdot e^{-kt} + \frac{k_1 \cdot A.}{\mathrm{k}}\left(1 - e^{-kt}\right) \tag{28}$$

$$\mathrm{C_0} = \mathrm{C_s} + \mathrm{C_{A0}} \tag{29}$$

where C is the content of not-yet-decomposed (or humified) SOM at time t, in tons; t is the time, in years; C_s is the quantity of stable organic matter carbon fraction in the soil at t = 0, in tons; C_{A0} is the initial active organic matter carbon fraction content at t = 0, in tons; C_0 is the initial total organic matter carbon content, in tons; A is the annual input of organic matter, in tons of dry matter; k_1 is the isohumic coefficient, characteristic of the composition of organic residues; and k is the mineralization coefficient of the active fraction.

4.1.10. SOMM Model

The SOMM is a theoretical analytical model for natural ecosystems that simulates the decomposition and transformation of organic matter in soil. It was developed as a theoretical tool to describe the natural ecosystem processes involving the decomposition of soil organic matter, mineralization, humification, and the release of carbon and nitrogen. This model assumes that SOM decomposition depends on energy and nutrient availability and environmental factors such as temperature, microorganisms, and moisture [125]. The model uses a set of linear differential equations with variable coefficients to predict the rate of decomposition and can be calibrated to specific soil types and management practices.

$$\frac{\mathrm{dL}}{\mathrm{dt}} = \mathrm{L_0} - (\mathrm{k_1} + \mathrm{k_3})\,\mathrm{L} \tag{30}$$

$$\frac{\mathrm{dF}}{\mathrm{dt}} = \mathrm{k_3L} - (\mathrm{k_2} + \mathrm{k_4} + \mathrm{k_5})\mathrm{F} \tag{31}$$

$$\frac{\mathrm{dH}}{\mathrm{dt}} = (\mathrm{k_4} + \mathrm{k_5})\mathrm{F}\,\mathrm{M_f} - K_6 H \tag{32}$$

where $\mathrm{L_0}$ is the litter input rate, L is the non-decomposed part of the litter remaining in the soil, F is the complex humic substance with non-decomposed plant debris, and H is the humus content. $\mathrm{K_1}$ and $\mathrm{k_2}$ are the relative rates of C losses from L (litter) and from F (complex humic substance). $\mathrm{K_3}$, $\mathrm{k_4}$, $\mathrm{k_5}$, and $\mathrm{k_6}$ are the relative decomposition rates for litter transformation to complex humic substances, complex humic substance consumption by microorganisms, complex humic substance consumption by earthworms, and humus mineralization, respectively. $\mathrm{M_f}$ is the fraction of complex humic substances transforming to humus. The relative rates of decomposition are modified for soil temperature and moisture content and for nitrogen and ash content of litter.

4.2. Simulation Models

Simulation models are based on computer programs that simulate the behavior of the system being modeled. These models operate on realistic assumptions and are more complex than analytical models. They are able to deal with a wide range of conditions and handle large and complex data [126]. They can provide more realistic and accurate predictions of SOM dynamics in response to different environmental conditions and management practices [49]. They are based on a more detailed approach and representation of soil ecosystems and use computer algorithms to simulate the biophysical and biochemical processes that control SOM dynamics, including microbial activity, plant residue decomposition, and soil structure formation, to explain the flux and distribution of carbon over a given time and scale [82].

4.2.1. Pernas's Model (1975)

Parnas [42] developed a model for the decomposition of organic material by microorganisms, which is among the first well-known simulation models. It considers SOM a heterogeneous mixture made up of different arbitrary pools that decompose at different rates.

$$R = C_1 + C_2 + N_1 = C + N_1 \text{ With } C = C_1 + C_2 \tag{33}$$

$$\frac{dR}{dt} = \frac{dC}{dt} + \frac{d\,\mathrm{N}_1}{dt} \tag{34}$$

$$\frac{dC}{dt} = -x{\cdot}G{\cdot}B \tag{35}$$

$$x = \frac{fc}{F} \tag{36}$$

where R is the organic matter subjected to decomposition, C_1 is the carbon per unit soil of substances made up of C-N (like proteins), C_2 is the carbon per unit soil of substances made up of C-C (like cellulose), N_1 is the amount of nitrogen in N-C compounds, B is the biomass of the decomposers per unit soil, G is the growth rate of the decomposers and depends on the C/N ratio of the organic matter, fc is the average fraction of carbon in the decomposer's cell, F is the ratio of carbon assimilated to carbon decomposed, and x is the total carbon used by the organisms per unit biomass increment.

4.2.2. The CENTURY Model

Parton et al. [127] developed an agroecosystem model that is a process-based model that simulates carbon and nutrient (carbon, nitrogen, sulfur, and phosphorus) cycling in soil–plant systems (in a grassland, crop, forest, or savanna over time scales of decades to millennia with monthly intervals) as well as crop growth. It describes the fate of carbon, nitrogen, water, sulfur, and phosphorus in soil compartments, such as living biomass, dead biomass, and SOM pools. The model simulates different effects of management practices on soil carbon sequestration, greenhouse gas emissions, and nutrient cycling. It has been applied to various ecosystems and management scenarios around the world [128–130]. The Century model consists of a set of differential equations that describe the flow of carbon and nitrogen through different pools (active, slow, and passive) in the soil, but nitrification is not included. The decomposition of all pools is described according to first-order kinetics with different relative rate constants per pool [110].

4.2.3. RothC Model

The Rothamsted Carbon Model (RothC) is a soil-organic-matter-simulation-process-based model that simulates the dynamics of carbon and nitrogen biogeochemistry in agroecosystems (soil–plant–atmosphere system) and is used to predict the effects of management practices on soil carbon storage and fluxes (predict crop growth, soil temperature and moisture, carbon dynamics, nitrogen leaching, and trace gases emissions) [131]. The RothC model deals with the turnover of organic carbon in non-waterlogged topsoil that allows for the effects of soil type, temperature, soil moisture, and plant cover on the turnover process. The model simulates SOM decomposition, humification, and mineralization. It predicts changes in soil carbon stocks in response to changes in land use, management, and climate. It is also used to estimate the potential for carbon sequestration through different agricultural practices. The model requires only a few inputs, which are almost readily available. It is an updated version of previous models developed by Jenkinson and Rayner in 1977 [85] and Hat 1984 [132]. It shares many similarities with other contemporary models of organic matter turnover, including CENTURY [129] and Van Veen and Paul's model [133]. Soil organic carbon can be divided into four active compartments and a small amount of inert organic matter (IOM). The active compartments are decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO), and humified organic matter (HUM). These compartments decompose with a first-order process at a specific rate, each. The rate of decomposition is not affected by the amount of organic matter added, and the priming action is assumed to be zero. The IOM compartment is resistant to decomposition [50].

4.2.4. Van Veen and Paul's Model (1981)

The Van Veen and Paul model is a conceptual model that describes the dynamics of soil organic matter. The model assumes that soil organic matter is composed of three fractions: active, slow, and passive. The active fraction is the most labile and readily decomposable, while the slow and passive fractions are progressively more resistant to decomposition. The model assumes that easily decomposable materials, such as cellulose and hemicellulose, are directly decomposed by the soil organisms. In contrast, the lignin fraction of aboveground residues and the resistant portion of the roots enter a decomposable native soil organic matter pool. This pool can be decomposed by the soil organisms or react with other soil constituents to form more recalcitrant soil organic matter. The model assumes that transformation rates are independent of biomass size and follow first-order kinetics. The model simulates the SOM transformations under native grassland conditions and predict the effect of agricultural management on organic matter levels. It divides SOM into different fractions that decompose at different rates controlled by a separate set of environmental factors, such as temperature, moisture, and substrate availability. The model has been used to understand the factors that regulate soil carbon storage and explore the potential of soil management practices, such as tillage and crop rotation, to affect soil organic matter dynamics [133]. The rate of decomposition of a substrate as described by first-order kinetics is

$$V = \frac{dC}{dt} = kC \tag{37}$$

where V is decomposition rate (quantity per time), C is the substrate (quantity), t is time, k is the rate constant.

When analyzing CO_2 output data to calculate decomposition rates, it considers biosynthesis as well. Biosynthesis, the process by which microorganisms use carbon from the soil to build new biomass, can affect the accuracy of decomposition rate estimates if not taken into account.

$$CO_T = CO_2[1 + \frac{Y}{100 - Y}] \tag{38}$$

where C is the actual amount decomposed, CO_2 is the CO_2 produced, and Y is the efficiency of the use of carbon for biosynthesis (is expressed as % of the total C uptake).

4.2.5. DND Model

The denitrification–decomposition model simulates the dynamic processes of carbon, nitrogen, and water cycling in terrestrial ecosystems. This model is employed in developing sustainable management strategies, assessing global change impacts, and simulating the effects of management practices on carbon and nitrogen cycling, carbon sequestration, and greenhouse gas emissions [134]. SOM pools consist of many sub-pools with different C/N ratios and relative rates of decomposition. The calculation of decomposition, CO_2 production, volatilized ammonia, and nitrification by decomposition sub-models is carried out daily. The denitrification sub-model calculates the production of N_2 and N_2O, and denitrification rates in the soil [134]. This model accounts for water flow as well as soil microorganisms' redox processes [135].

4.2.6. DayCent Model

The DayCent model is the daily time-step version of the Century model. It simulates the agroecosystem (atmosphere, plants, and soil) processes and the dynamics of carbon, phosphorus, nitrogen, sulfur, CO_2, CH_4, N_2O, NO_x, and N_2 over time. It helps in assessing the impacts of management practices on productivity, greenhouse gas emissions, and climate change from agricultural systems. It integrates mechanistic models of crop growth with soil water, carbon, and nitrogen dynamics. It is capable of simulating crop rotations, fertilizer and manure applications, and irrigation management. DayCent can also be used to incorporate the effects of climate variability on crop and soil processes. It takes into account a wide range of environmental and management factors that influence ecosystem carbon and nitrogen dynamics, including climate, soil properties, vegetation type and management practices such as tillage and fertilization. DayCent modeling equations are used to simulate crop growth and soil processes over long time scales [136–138].

4.2.7. Yasso Model

The Yasso model divides SOM into two pools decomposing at different rates and that reduces with the formation of recalcitrant fractions, the labile and stable one. It takes into account the SOM fractions' turnover time considering the organic material availability, its quality, and climate data. This model simulates the long-term change in SOM as a result of land management practices [139]. Organic material decomposition does not only depend on its chemical characteristics but also on its physical characteristics and exposure to microbial decomposition; as decomposition goes on, organic materials lose weight; decomposed mass of organic material is removed from the soil and there is formation of more complex recalcitrant compounds; lastly, temperature and moisture affect decomposition processes [140].

4.2.8. ANIMO Model

The ANIMO (agricultural nutrient model) model is an advanced mathematical model for predicting the behavior of organic matter in soil. It considers the soil and hydrological conditions, management practices, fertilizers, nutrient leaching, environmental factors, and biochemical processes (C, N, and P cycles; decomposition) to simulate SOM dynamics and carbon sequestration, and to improve agricultural productivity. The model was developed by adding a humification term to the conventional first-order kinetic model of SOM decomposition, which allows for a more realistic simulation of SOM dynamics [141–143]. The ANIMO model involves a set of differential equations that describe the changes in organic matter pools in nature, forest, and agricultural soils over time, and the user has to define the pools and parameters.

4.2.9. CANDY Model

The carbon and nitrogen dynamics model simulates long-term carbon and short-term nitrogen cycling in soil. It is made up of different sub-models that represent biophysicochemical and environmental processes from a range of different agroecosystems. The model divides SOM into different categories of pools including fresh, biologically active, and slow-cycling organic matter. Each one of these pools decompose according to the first-order kinetics with the rate constants depending on the environment, and carbon and nitrogen move through these three pools according to pool C/N ratio, nitrogen mineralization and immobilization, and carbon dioxide release [144,145]. Its sub-models include the soil temperature model, hydrological model, crop model, and SOM turnover model, including the nitrogen model [144].

Soil temperature sub-model:

$$\frac{d(CT)}{dt} = \frac{d}{dz}\left(\alpha \frac{d\mathrm{T}}{dz}\right) \tag{39}$$

where t, time (d); z, depth (cm); C, volumetric heat capacity of soil (J cm^{-3} K); T, soil temperature (K); α, thermal conductivity (J S^{-1} cm^{-1} K^{-1}).

Hydrological sub-model:

$$\frac{dW}{dt} = \lambda(W - W_{FK})^2,\ W \geq W_{FK} \tag{40}$$

where t, time; W, water content (mm) of a soil column of defined thickness; W_{FK}, water content at field capacity (mm); λ, drainage parameter (mm^{-1} d^{-1})

Crop sub-model:

$$N_{upt}(t) = 0.5\left(1 - \frac{\tanh\left(\frac{2t}{V} - 1\right)S}{\tanh(S)}\right)N_{yield} \tag{41}$$

where N_{upt}, total nitrogen in the crop (kg N ha^{-1}); t, time (d, with zero at the beginning of plant uptake); N_{Yield}, total nitrogen uptake at harvest (kg N ha^{-1}); V (d), the crop-dependent length of the vegetation period; S, a crop parameter; and tanh, the hyperbolic tangent function.

Nitrogen dynamics sub-model:

$$\frac{dC_{AOM}(t)}{dt} = -K_{AOM}C_{AOM}(t) \tag{42}$$

$$\frac{dC_{BOM}(t)}{dt} = \eta K_{AOM}C_{AOM}(t) - (K_{BOM} + K_S)C_{BOM}(t) + K_a C_{SOM}(t) \tag{43}$$

$$\frac{dC_{SOM}(t)}{dt} = K_S C_{BOM}(t) - K_a C_{SOM}(t) \tag{44}$$

where AOM, the added organic matter; BOM, the biologically active soil organic matter; SOM, the stabilized soil organic matter; C, the C contents of the corresponding compartments of soil organic matter (kg C ha^{-1}); K, the rate coefficients (d^{-1}), depending on soil temperature and moisture content; and η, the dimensionless synthesis coefficient.

4.2.10. Root Zone Water Quality Model

This is an agricultural system simulation model that deals with agricultural production by taking into account the environment, interactions, movement, and fate of water, nutrients, pesticides, and crops. It distinguishes five carbon and nitrogen pools and simulates their transformation in the soil system. The decomposition of residue (two pools) and organic matter (three pools), as well as denitrification, follow the first-order reaction kinetics. However, nitrification follows zero-order reaction kinetics with changing specific rate coefficients according to conditions. The net assimilation is calculated from the C/N ratio in the five pools, taking into account that part of the carbon is assimilated into microbial biomass. The model also considers the growth and energy sources (pools, nitrification) of hetero- and autotrophs in the system [146].

4.2.11. PAPRAN Model

The PAPRAN model divides soil organic matter into two main components with different decomposition rates and contributions to soil nutrients: labile and recalcitrant. The decomposition of soil organic matter follows the first-order reaction kinetics and takes into account the effects of soil temperature, moisture, and pH. PAPRAN uses a combination of empirical and mechanistic equations to simulate the processes of decomposition, mineralization, and immobilization of organic matter and nitrogen in soil. The model requires input data such as soil type, climate, crop history, and management practices to parameterize the model and simulate SOM and nitrogen dynamics over time [147,148].

4.2.12. NCSOIL Model

The nitrogen and carbon transformation in soil (NCSOIL) model simulates the dynamics of nitrogen and carbon transformations in the soil–water–air–plant system. The model considers soil organic matter made of fresh plant derivatives, microbial biomass, and active and recalcitrant pools. These pools decompose independently and according to the available nitrogen. The model allows for choosing between first-order and Monod-type reaction kinetics for organic matter decomposition [149]. Overall, the NCSOIL model is a useful tool for understanding the complex interactions between soil, plants, and microorganisms, and for developing sustainable agricultural practices that support both productivity and environmental conservation.

4.2.13. DAISY Model

The DAISY model is a crop growth model that simulates the decomposition and mineralization of soil organic matter in agricultural soils taking into account the C/N ratio, water, and heat flow for the wet temperate climate of north-West Europe. The model considers key environmental factors, including temperature and moisture, as well as crop residue inputs, and its sub-pool decomposition and transformation processes are based on first-order reaction kinetics and substrate use efficiency [150].

4.2.14. SUNDIAL Model

The SUNDIAL (Simulation of Nitrogen Dynamics in Agricultural Landscapes) model is based on the Rothamsted carbon model. It simulates SOM dynamics but also includes nitrogen cycling and crop growth in agricultural systems [151]. The model utilizes differential equations to describe the rates of soil organic matter decomposition, nitrogen mineralization, and plant uptake. Specifically, the decomposition process is represented by three pools, each characterized by first-order kinetics.

4.2.15. ECOSYS Model

The ECOSYS model is a process-based model for natural and managed ecosystems that take into account various factors such as soil water, heat, carbon, oxygen, nitrogen, phosphorus, some ion transport, and gases exchange in agricultural management systems. It takes into account physical and biological processes at different scales and simulates the dynamics of soil organic matter, carbon sequestration, and greenhouse gas emissions in an ecosystem by considering the balance between inputs, outputs, and losses of soil organic matter [152]. This model divides SOM into four substrates or pools—active, passive, animal, and plant derivatives—that can exist in different states (solid, soluble, adsorbed, and microbial). These substrates decompose according to factors such as cellulose, lignin, clay, carbohydrates content, available water and temperature, and the substrate–microbe-density relationship. The model also classifies microbes into four categories: obligate anaerobic, obligate aerobic, facultative anaerobic, and methanogens. To describe the rates of soil organic matter decomposition, humification, carbon inputs from plants, and microbial processes, the model uses differential equations that are dependent on the substrate–microbe relationship [153].

4.2.16. APSIM Model

This is an agricultural production systems simulator for managing crops, forests, pastures, and soils in agricultural systems. It simulates biophysical processes in agricultural systems focusing on ecological and economic effects of agricultural practices vis-a-vis climate [154]. APSIM is structured around plant, soil, and management modules. These modules include a diverse range of crops, pastures, and trees, soil processes including water balance, N and P transformations, soil pH, erosion, and a full range of management controls. The Soil N module describes soil organic matter and deals with nitrogen mineralization through three pools: fresh, active, and stable organic matter. The Residue module deals with the effect of residue on soil and water. The transfer of carbon and nitrogen between these pools depends on factors such as C/N content, decomposition, mineralization, immobilization, plant growth, soil water movement, and nutrient cycling [155].

5. A Synopsis of the Strengths, Limitations, and Applications of Some Analytical and Simulation-Based Soil Organic Matter Modeling Approaches in Understanding and Predicting SOM Dynamics

Soil organic matter modeling approaches offer valuable insights into the dynamics of SOM and its role in soil health and productivity. By examining the strengths, limitations, and applications of different modeling approaches, researchers can enhance their understanding of SOM dynamics and make more accurate predictions [156,157].

The strengths of SOM modeling approaches lie in their ability to integrate various factors and processes influencing SOM dynamics, such as decomposition, mineralization, and stabilization. These models provide a framework for quantifying and analyzing the complex interactions between soil properties, climate, land management practices, and SOM dynamics. They allow researchers to simulate different scenarios and assess the effects of management practices on SOM content and quality [49,158].

However, it is important to acknowledge the limitations of SOM modeling approaches. Models rely on input data, which may have inherent uncertainties and variability. The accuracy of the models depends on the quality and availability of data, as well as the assumptions and simplifications made during model development. Additionally, models may have limitations in representing specific soil types or ecosystems, and their predictive power may vary depending on the scale of analysis [49].

Despite these limitations, SOM modeling approaches have diverse applications. They can be used to evaluate the impacts of different management practices on SOM dynamics, assess the effectiveness of soil conservation and carbon sequestration strategies, and support decision-making processes for sustainable land management. Models also contribute to our understanding of the long-term dynamics of SOM and its role in climate change mitigation and adaptation [159].

Briefly, a synopsis of strengths, limitations, and applications of SOM modeling approaches provides valuable insights into the complexity of SOM dynamics (Table 2). By considering these factors, researchers can refine and improve the accuracy of models, leading to more effective strategies for sustainable soil management and enhanced soil health [82].

Table 2. Strengths, limitations, and applications of analytical and simulation soil organic matter modeling approaches.

Models	Strengths	Limitations	Applications
Analytical Models	Easily understandable and interpretable. Requires limited data and information. Suitable for small-scale studies. Can be used to predict long-term SOM dynamics.	Limited scope of applicability. Assumptions are often oversimplified and sometimes unrealistic. Inability to capture the complexity of real-world	Predicting decomposition rate, transformation, lability, and stability of SOM. Quantifying the impact of management practices on SOM. Evaluating the effects of climate change and land-use changes on SOM
Hénin and Dupuis model (1945)	Provides a simple and intuitive representation of soil organic matter dynamics. Applicable for different soil types. Can be used to estimate SOM turnover time.	Ignoring environmental factors during SOM decomposition.	Useful as a historical reference for the development of soil carbon models. Can be used as a baseline model for more complex soil carbon models. Predicting carbon and nitrogen mineralization rates
Kortleven Model (1963)	Can be used for predicting nitrogen mineralization. Simple and easy to use.	Assumptions are oversimplified. Ignores the impact of environmental factors	Predicting nitrogen mineralization and SOM decomposition rates in different soils
Kolenbrander Model (1969)	Suitable for estimating nitrogen immobilization rate. Incorporates environmental factors such as pH and temperature.	Assumes a constant microbial biomass. Limited scope of applicability	Predicting nitrogen immobilization rate and SOM decomposition rate under different management practices and soil conditions
Godshalk Model (1977)	Simple and easy to use. Applicable for predicting carbon and nitrogen mineralization.	Assumes constant environmental conditions. Limited scope of applicability	Predicting SOM decomposition rates in different soils under varying environmental conditions
Jansen Model (1984)	Incorporates the effects of temperature and moisture. Suitable for estimating long-term SOM dynamics	Limited scope of applicability, Assumes a constant microbial biomass	Predicting SOM decomposition and mineralization rates, and carbon balance under varying environmental conditions. Assessing management practices in mitigating climate change.
ICBM (Introductory Carbon Balance Model), Andrén and Kätterer model (1997)	Accounts for the effects of temperature and moisture. Suitable for predicting long-term SOM dynamics. Account for carbon balance at various spatial scales, from individual plants to entire ecosystems. It incorporates a detailed understanding of plant physiology and ecosystem processes.	Requires a lot of detailed input data and parameters (vegetation characteristics, climate, and soil properties). Limited scope of applicability and its calibration can be complex and time-consuming.	Predicting SOM decomposition and mineralization rates under different management practices and environmental conditions

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
Andriulo Model (1999)	Incorporates temperature and moisture effects. Suitable for predicting long-term SOM dynamics.	Limited scope of applicability. Assumes a constant microbial biomass	Predicting SOM decomposition and mineralization rates under different management practices and environmental conditions
SOMM (Soil Organic Matter Mineralization) model	Incorporates a detailed understanding of microbial ecology and soil organic matter dynamics. It can simulate the decomposition and mineralization of different fractions of organic matter, including labile and recalcitrant pools. Suitable for predicting long-term SOM dynamics.	Model calibration can be complex, as it requires detailed information on soil characteristics and microbial processes. Input data requirements can be high, including detailed information on soil texture, structure, and water content.	Useful for understanding and predicting the effects of management practices, such as tillage, fertilization, and crop rotation, on soil organic matter dynamics. Can be used to assess the impacts of climate change on soil organic matter mineralization rates. Predicting SOM dynamics under different land-use scenarios
Sauerbeck and Gonzalez model (1977)	Simple and easy to use, with few input data requirements. Can be used to estimate soil carbon turnover rates and the decomposition of different soil organic matter fractions.	Does not account for the effects of environmental factors, such as temperature and moisture, on soil organic matter decomposition. Assumes a fixed rate of carbon loss from the soil organic matter pool, which may not reflect actual soil carbon dynamics.	Useful for comparing the turnover rates of different soil organic matter fractions and estimating the potential impact of changes in management practices on soil carbon storage. Can be used as a baseline model for more complex soil carbon models.
Yang Model (1996)	Can be used for predicting long-term SOM dynamics. Accounts for the effects of temperature and moisture.	Limited scope of applicability. Assumes a constant microbial biomass	Predicting SOM dynamics under different land use and management practices
Simulation Models	Can capture the complexity of real-world systems. Can incorporate various environmental factors. Can be used to simulate various management practices	Require large amounts of input data and parameters. Difficult to interpret and explain. Limited to specific soil types	Predicting SOM dynamics at large spatial and temporal scales. Evaluating the effects of climate change and land-use changes on SOM. Predicting the impact of different management practices on SOM
Pernas model (1975)	Provides a simple and intuitive representation of soil organic matter dynamics and mineralization. Can be used to estimate the decomposition rates of different soil organic matter fractions.	Assumes that soil organic matter decomposes at a constant rate, which does not reflect actual soil carbon dynamics. Does not account for the effects of environmental factors, such as temperature and moisture, on soil organic matter decomposition. Limited scope of applicability.	Useful as a historical reference for the development of soil carbon models. Can be used as a baseline model for more complex soil carbon models. Predicting SOM decomposition and mineralization rates under different environmental conditions

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
CENTURY model	Accounts for the effects of environmental factors, such as temperature, moisture, and land use, on soil organic matter decomposition. Can simulate the impacts of different management practices on soil carbon storage. Can simulate soil carbon dynamics over long time scales (e.g., centuries).	Requires a large amount of input data, including soil properties, climate data, and management practices. Can be computationally intensive, particularly when simulating large spatial and temporal scales. May not accurately represent soil carbon dynamics in certain soil types or regions.	Widely used in global climate models and to evaluate the impacts of land use and management on soil carbon storage. Can be used to develop management strategies to enhance soil carbon storage and mitigate climate change.
RothC model	Accounts for the effects of temperature, moisture, and soil properties on soil organic matter decomposition. Can be used to simulate soil carbon dynamics under different management practices. Can simulate soil carbon dynamics over long time scales (e.g., centuries). Includes an option to incorporate soil respiration measurements to calibrate the model.	Requires input data on soil properties, climate data, and management practices. Can be computationally intensive, particularly when simulating large spatial and temporal scales. May not accurately represent soil carbon dynamics in certain soil types or regions.	Used to evaluate the impacts of land use and management on soil carbon storage. Can be used to develop management strategies to enhance soil carbon storage and mitigate climate change.
Van Veen and Paul model (1981)	Can predict SOM dynamics under different management practices	Limited scope of applicability. Assumes a constant microbial biomass	Predicting SOM dynamics under different management practices and environmental conditions
DNDC Model	Can simulate the effects of climate change and land-use changes	Requires large amounts of input data and parameters. Model structure is complex and difficult to modify.	Predicting SOM dynamics under different land-use and climate scenarios
DayCent Model	Suitable for predicting SOM dynamics under different management practices and environmental conditions	Requires large amounts of input data and parameters. Model structure is complex and difficult to modify	Predicting SOM dynamics under different management practices and environmental conditions
Yasso model	Accounts for the effects of temperature, moisture, and litter quality on soil organic matter decomposition. Can simulate the impacts of different management practices on soil carbon storage. Can simulate soil carbon dynamics over long time scales (e.g., centuries). Includes an option to incorporate field measurements to calibrate the model.	Requires input data on litter quality, climate data, and management practices. May not accurately represent soil carbon dynamics in certain soil types or regions. Does not explicitly account for the effects of soil properties on soil carbon dynamics.	Widely used in global carbon cycle models and to evaluate the impacts of land use and management on soil carbon storage. Can be used to develop management strategies to enhance soil carbon storage and mitigate climate change.

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
ANIMO model	Can simulate the effects of different land use and management practices on soil carbon dynamics. Includes options to account for the effects of climate change and elevated atmospheric CO_2 on soil carbon storage. Can simulate soil carbon dynamics over long time scales (e.g., centuries). Includes an option to incorporate field measurements to calibrate the model.	Requires input data on soil properties, climate data, and management practices. May not accurately represent soil carbon dynamics in certain soil types or regions. Does not account for the effects of soil biota on soil carbon dynamics.	Widely used in global carbon cycle models and to evaluate the impacts of land use and management on soil carbon storage. Can be used to develop management strategies to enhance soil carbon storage and mitigate climate change.
CANDY model	Can simulate the effects of different land use and management practices on soil carbon dynamics. Accounts for the effects of temperature, moisture, and litter quality on soil organic matter decomposition. Can simulate soil carbon dynamics over long time scales (e.g., centuries). Includes an option to incorporate field measurements to calibrate the model.	Requires input data on soil properties, climate data, and management practices. May not accurately represent soil carbon dynamics in certain soil types or regions. Does not explicitly account for the effects of soil biota on soil carbon dynamics.	Widely used in global carbon cycle models and to evaluate the impacts of land use and management on soil carbon storage. Can be used to develop management strategies to enhance soil carbon storage and mitigate climate change.
Root Zone Water Quality Model	Can simulate the transport and fate of nutrients, pesticides, and other contaminants in soil and groundwater. Accounts for the effects of soil properties, land use, and management practices on soil water and solute transport. Allows for the evaluation of management strategies to reduce non-point-source pollution. Includes user-friendly interface and graphical output.	Requires input data on soil properties, crop management practices, and hydrologic conditions. Does not explicitly account for the effects of soil biota on nutrient cycling and pollutant degradation. May not accurately represent soil water and solute transport in certain soil types or regions.	Widely used by researchers, consultants, and policymakers to assess the impacts of agricultural management practices on water quality. Can be used to evaluate the effectiveness of best management practices (BMPs) to reduce non-point source pollution.

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
PAPRAN Model	Simulates the growth and production of annual pastures under different climatic and management conditions. Accounts for the effects of rainfall, temperature, and nitrogen availability on pasture growth and quality. Can be used to optimize fertilization and grazing management practices to maximize pasture productivity and quality. Allows for the assessment of the potential impact of climate change on pasture production.	Does not account for the effects of other environmental factors, such as soil fertility and pests, on pasture growth and quality. May require calibration to local conditions to accurately represent pasture growth and quality.	Can be used by farmers and land managers to optimize pasture management practices and improve productivity. Can be used to assess the impact of climate change on pasture production and inform adaptation strategies.
NCSOIL Model	Accounts for the interactions between carbon and nitrogen cycles in soil. Simulates the mineralization, immobilization, and nitrification of soil organic matter and nitrogen. Allows for the evaluation of the impact of management practices and environmental factors on soil carbon and nitrogen dynamics.	Requires detailed information on soil properties and management practices to accurately simulate soil carbon and nitrogen dynamics. May not accurately represent the effects of other environmental factors, such as temperature and moisture, on soil carbon and nitrogen dynamics.	Can be used to optimize management practices to increase soil carbon sequestration and reduce nitrogen losses. Can be used to assess the potential impact of climate change on soil carbon and nitrogen dynamics and inform adaptation strategies.
DAISY Model	Accounts for the aerobic and anaerobic microbial activity in soil. Simulates the decomposition and mineralization of soil organic matter, nitrogen transformations, and soil water dynamics. Can be used to simulate the effects of management practices, such as irrigation and fertilization, on soil carbon and nitrogen dynamics.	Requires detailed information on soil properties and management practices to accurately simulate soil carbon and nitrogen dynamics. May not accurately represent the effects of other environmental factors, such as temperature and moisture, on soil carbon and nitrogen dynamics.	Can be used to optimize management practices to increase soil carbon sequestration and reduce nitrogen losses. Can be used to assess the potential impact of climate change on soil carbon and nitrogen dynamics and inform adaptation strategies.
SUNDIAL Model	Simulates the dynamics of carbon, nitrogen, phosphorus, and water in agricultural landscapes. Accounts for multiple environmental factors, such as temperature, precipitation, and soil properties, that affect nutrient cycling. Can be used to simulate the effects of management practices, such as crop rotation and fertilizer application, on nutrient cycling and water quality.	Requires detailed information on soil properties, climate, and management practices to accurately simulate nutrient cycling and water quality. May not accurately represent the effects of other environmental factors, such as land-use changes, on nutrient cycling and water quality.	Can be used to optimize management practices to improve nutrient cycling and water quality in agricultural landscapes. Can be used to assess the potential impact of climate change and land-use changes on nutrient cycling and water quality and inform adaptation and mitigation strategies.

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
ECOSYS Model	Simulates the exchange of carbon, water, and energy between the land surface and the atmosphere. Accounts for multiple environmental factors, such as temperature, precipitation, and soil properties, that affect ecosystem processes. Can be used to simulate the effects of management practices, such as land-use change and vegetation management, on ecosystem processes and carbon sequestration.	Requires detailed information on soil properties, climate, and vegetation characteristics to accurately simulate ecosystem processes. May not accurately represent the effects of other environmental factors, such as nutrient availability and disturbance regimes, on ecosystem processes.	Can be used to assess the potential for carbon sequestration in different ecosystems and under different management practices. Can be used to inform land-use planning and policy development aimed at mitigating climate change.
APSIM Model	Can simulate a wide range of agricultural production systems, including crops, pastures, and livestock. Accounts for multiple environmental factors, such as soil properties, climate, and management practices, that affect crop growth and yield. Includes modules for simulating soil water and nutrient dynamics, crop growth and development, and pest and disease interactions.	Requires detailed information on soil properties, climate, and management practices to accurately simulate crop growth and yield. May not accurately represent the effects of extreme weather events or other unpredictable environmental factors on crop production.	Can be used to assess the effects of different management practices, such as crop rotation and irrigation, on crop growth and yield. Can be used to evaluate the potential impacts of climate change on agricultural production and inform adaptation strategies.
NICCCE (Nitrogen isotopes and carbon cycling in coniferous ecosystems)	The model integrates carbon and nitrogen cycles and explicitly considers the effects of isotopic fractionation, allowing for the analysis of isotopic patterns in the soil and vegetation. The model can be used to simulate the impacts of changes in environmental conditions (e.g., temperature, precipitation, nitrogen deposition) on carbon and nitrogen dynamics in coniferous ecosystems. The model has been extensively tested and validated against field measurements, demonstrating its ability to accurately predict carbon and nitrogen dynamics in coniferous ecosystems.	The model has only been tested in coniferous ecosystems, so its applicability to other ecosystem types is unclear. The model requires a large amount of input data, including site-specific parameters such as soil texture and vegetation characteristics, which can be time-consuming and costly to collect. The model assumes that all carbon and nitrogen inputs and outputs are isotopically distinct, which may not always be the case in the real world.	The model can be used to investigate the impacts of environmental changes on carbon and nitrogen cycling in coniferous ecosystems, including the effects of climate change, nitrogen deposition, and forest management practices. The model can be used to explore the isotopic patterns in soil and vegetation to gain insights into the sources and cycling of carbon and nitrogen in coniferous ecosystems. The model can be used to develop management strategies for coniferous ecosystems that aim to optimize carbon and nitrogen sequestration and reduce greenhouse gas emissions.

Table 2. *Cont.*

Models	Strengths	Limitations	Applications
EPIC (Erosion Productivity Impact Calculator) Model	Integrates various processes, including erosion, climate, soil, and crop management, to simulate soil and crop productivity. Incorporates spatial variability of soil properties and weather data to improve accuracy of simulations. Allows for simulating long-term effects of land-use changes and management practices on soil and crop productivity. Has been widely used and tested in various regions across the world.	Data-intensive and requires input data for various variables, which can be difficult to obtain. Calibration of model parameters can be time-consuming and may require extensive field measurements. Requires expertise in modeling and agricultural sciences to use and interpret results. Does not account for all soil and crop processes, such as nutrient cycling and root growth, and may require additional models for more comprehensive analyses.	Used for a wide range of applications, including crop management, land-use planning, and environmental impact assessments. Used in various regions across the world for predicting crop yields and environmental impacts. Used for evaluating the impacts of climate change and extreme weather events on crop productivity. Used for assessing the economic and environmental impacts of agricultural practices and policies
Osnabruck Model	Considers soil organic matter decomposition and nutrient cycling processes in detail. Accounts for the impact of management practices on soil organic matter dynamics. Applicable to various soil types and climatic conditions. Allows for the simulation of different plant species and cropping systems.	Requires input data on soil properties and management practices that can be time-consuming and costly to collect. Limited validation and testing under different environmental conditions. Does not account for the influence of soil microorganisms on soil organic matter dynamics.	Can be used to evaluate the effects of different management practices on soil organic matter and nutrient cycling. Useful in predicting the long-term impacts of land-use and management changes on soil quality. Can aid in developing sustainable agricultural practices.
Verberne model	Includes management practices such as tillage, crop rotation, and fertilization. Accounts for different types of organic matter and their decomposition rates. Incorporates environmental factors such as temperature and moisture	Limited validation in certain regions and soil types. Requires input data that may not always be readily available	Assessing the impacts of management practices on soil organic matter dynamics. Predicting the effects of environmental changes on soil carbon storage

6. Conclusions and Future Perspectives

Soil organic matter is widely recognized as a key indicator of soil quality and serves as both a source and sink of carbon. Understanding the quality and quantity of SOM pools, as well as their stability and lability, is crucial in comprehending the roles they play in nutrient cycling, soil health, environmental changes, and water storage capacity. However, the conflict between maintaining or increasing soil organic matter and the effects of management practices on SOM requires further investigation and resolution in different land-use systems. This is particularly crucial for sustainable soil management and for developing models that can accurately capture the quantitative and qualitative changes of SOM.

Characterizing SOM quality, composition, and quantity requires, on one the hand, examining the physical, biological, and chemical properties of the soil and its organic compounds, which helps to explore SOM fractions and characterize their molecular structure and composition. This helps identify the processes that contribute to SOM formation and decomposition and their effects on soil functions. On the other hand, it also involves measuring the total amount of soil carbon (quantitative methods) as well as evaluating its dynamics over time. However, as the quantitative methods do not inform us about SOM quality or composition, a combination of both methods is necessary for a comprehensive analysis of SOM and its importance in maintaining soil health and sustainability.

In the same vein, soil organic matter (SOM) modeling offers a valuable approach for predicting and understanding the dynamics of SOM and developing sustainable soil management strategies. By incorporating data on soil properties and climate, vegetation, and management practices, models can simulate the decomposition, mineralization, and stabilization rates of organic matter in soil. This enables researchers and land managers to assess the effects of different practices and environmental factors on SOM availability, composition, and turnover. The use of models can support the analysis of changes in SOM content and quality under various scenarios, aiding in the development of more sustainable land-use strategies. However, the accurate calibration and validation of models are essential to ensure their reliability and applicability to specific soil and environmental conditions. By optimizing soil organic carbon levels and nutrient recycling, informed land management strategies can be developed to enhance soil productivity and maintain long-term soil health.

Future research directions should include improved model parameterization, the integration of multi-scale modeling, the incorporation of emerging technologies, the assessment of climate change impacts, the integration of socioeconomic factors, validation and benchmarking, and interdisciplinary collaborations.

This is because enhancing the accuracy of SOM models requires better parameterization, particularly in terms of soil properties, climate inputs, and management practices. Future research should focus on obtaining high-quality and comprehensive data to refine model parameters and reduce uncertainties.

Incorporating multi-scale modeling approaches can provide a more holistic understanding of SOM dynamics. Integrating models that operate at different spatial and temporal scales, from the micro-scale of soil aggregates to landscape-level assessments, can improve predictions and facilitate more effective decision making.

Advancements in sensor technologies, remote sensing, and data analytics offer new opportunities for monitoring and assessing SOM dynamics. Future research should explore the integration of these technologies into SOM modeling frameworks to improve data collection, validation, and model calibration.

Climate change poses significant challenges to SOM dynamics, as it can influence decomposition rates, nutrient cycling, and carbon sequestration. Future research should focus on understanding the interactions between climate change and SOM dynamics to develop climate-resilient management strategies.

Considering socioeconomic factors, such as farmer behavior, market dynamics, and policy frameworks, in SOM modeling can provide a more comprehensive assessment of the impacts of agricultural practices on SOM dynamics. Future research should explore the integration of socioeconomic models with biophysical models to capture the feedback loops between human activities and SOM dynamics.

The robust validation and benchmarking of SOM models are crucial for assessing their accuracy and reliability. Future research should prioritize extensive field validation studies using long-term monitoring data and experimental manipulations to ensure the models capture the complexity of real-world SOM dynamics.

The collaboration between soil scientists, ecologists, agronomists, economists, and social scientists can enrich the understanding of SOM dynamics and its implications for sustainable land management. Future research should foster interdisciplinary collaborations to address the complex challenges associated with SOM modeling and inform policy and management decisions.

By focusing on these future research directions, scientists can advance our understanding of SOM dynamics, improve the accuracy of modeling approaches, and contribute to the development of sustainable soil management strategies in the face of global environmental changes.

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