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Incorporating Biochar Into Biogeochemical Models: Achievements and Challenges

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ABSTRACT

In the last two decades, several studies have utilized biogeochemical models to evaluate the impact of different edaphoclimatic conditions on soil carbon storage and the dynamics of soil organic carbon. At the same time, biochar, a carbon-rich material obtained from the pyrolysis of biomass residues, has been identified as a promising carbon sequestration material. However, current models do not adequately incorporate the role of biochar in soil management. In this context, the current state of research on biogeochemical models that include the entry of biochar into soil has been characterized. The research indicated that the development of studies on the topic "biochar" is widely explored, with 4259 papers being identified using the first search filter. Specifically, searching for studies that mentioned terms related to biogeochemical models for estimating soil carbon stock, it was observed that a small number of the studies ($N = 46$) considered the entry of biochar into the models. Although most studies have used the RothC model to simulate biochar within biogeochemical models, biochar inputs have also been implemented in APSIM, EPIC, Century, DNDC, and other models, including those not primarily focused on soil carbon stock estimation. Among these studies, the minority included the results of calibration and validation of the models, which are paramount for the model's credibility. Therefore, efforts must be concentrated on solving the lack of valuable data to validate the models. Data from long-term field experiments that consider interactions between crop and climate conditions are highly desirable. The possibility of increasing carbon stocks by incorporating biochar into the soil could promote environmental and financial gains, and biogeochemical models that consider the incorporation of biochar are valuable tools for decision-makers.

1 | Introduction

Soil carbon (C) storage plays a crucial role for mitigating global climate change, and depending on the land use and management practices, can act as a source or sink of greenhouse gas (GHG) emissions (IPCC 2019). Improving land use and soil management in agriculture can increase soil C stocks and mitigate climate change (Ma et al. 2023). Several practices have been proposed worldwide as strategies to increase soil C stocks in the long term, including the application of biochar (Paustian et al. 2016). Biochar, the solid product of biomass pyrolysis, is considered a highly viable climate-smart solution (IPCC et al. 2019; Joseph et al. 2021; Lehmann 2007; Smith 2016; Fouché et al. 2023). In addition to its contribution to C sequestration, biochar application has been shown to enhance soil fertility and positively influence agricultural productivity, as demonstrated by several studies (Yang et al. 2025; Xu et al. 2025).

To understand why biochar supports soil C storage, it is necessary to consider the photosynthetic process in which the carbonaceous metabolites and biomass produced by plants return to CO_2 when the plant-derived materials are decomposed (Figure 1). In the pyrolysis process, plant residues are thermally degraded in an environment with limited oxygen, promoting structural reorganization of the material, which promotes C storage in a stable form.

Biochar consists of stacked polycondensed aromatic C structures, including crystalline graphene sheets and amorphous aromatic structures (Conte et al. 2021). The mineralization of this carbonaceous material back to CO_2 is extremely slow (Conte et al. 2021; Lehmann et al. 2011). Estimating the potential for C sequestration by incorporating biochar is necessary to predict its stability in soils. While biochar properties are the primary determinant of its persistence compared to the mineralization of nonpyrolyzed biomass, edaphic and climatic factors also play a significant role (Joseph et al. 2021). Therefore, a comprehensive understanding of soil–crop–climate–biochar interactions at the systems level is essential to predict if C stock responses will be positive, negative, or neutral (Archontoulis et al. 2016). Relying solely on field measurements to grasp these intricate interactions can be highly challenging and expensive.

Traditionally, basic empirical models have been employed to assess biochar stability and the resulting C accumulation within the soil. Seeking to enhance the biochar assessment framework, Woolf et al. (2021) developed the model by incorporating a broader analysis of existing research and expanding parameterization for biochar persistence estimation. Their methodology, relying on meta-analysis and curve fitting of incubation studies, yields estimates of the fraction of biochar C retained in the soil (Fperm) at 100, 500, and 1000 years. This enhanced approach is now integral to several biochar certification schemes, such as the Puro. earth and Verra VCS.

Nonetheless, empirical equations for biochar stability assessment have limitations, as recently highlighted by Sanei et al. (2025) and Ringsby and Maher (2025). Specifically, current models fail to adequately represent the complex biochar degradation process, particularly the presence of a recalcitrant C fraction with decomposition rates below the detection threshold in short-term incubation studies. This discrepancy compromises the correlation between biochar stability and the degree of carbonization, potentially leading to an underestimation of the C sequestration potential. Therefore, the improvement and use of biogeochemical mathematical models that consider the complex interactions among soil, biochar, plants, and edaphoclimatic conditions are essential.

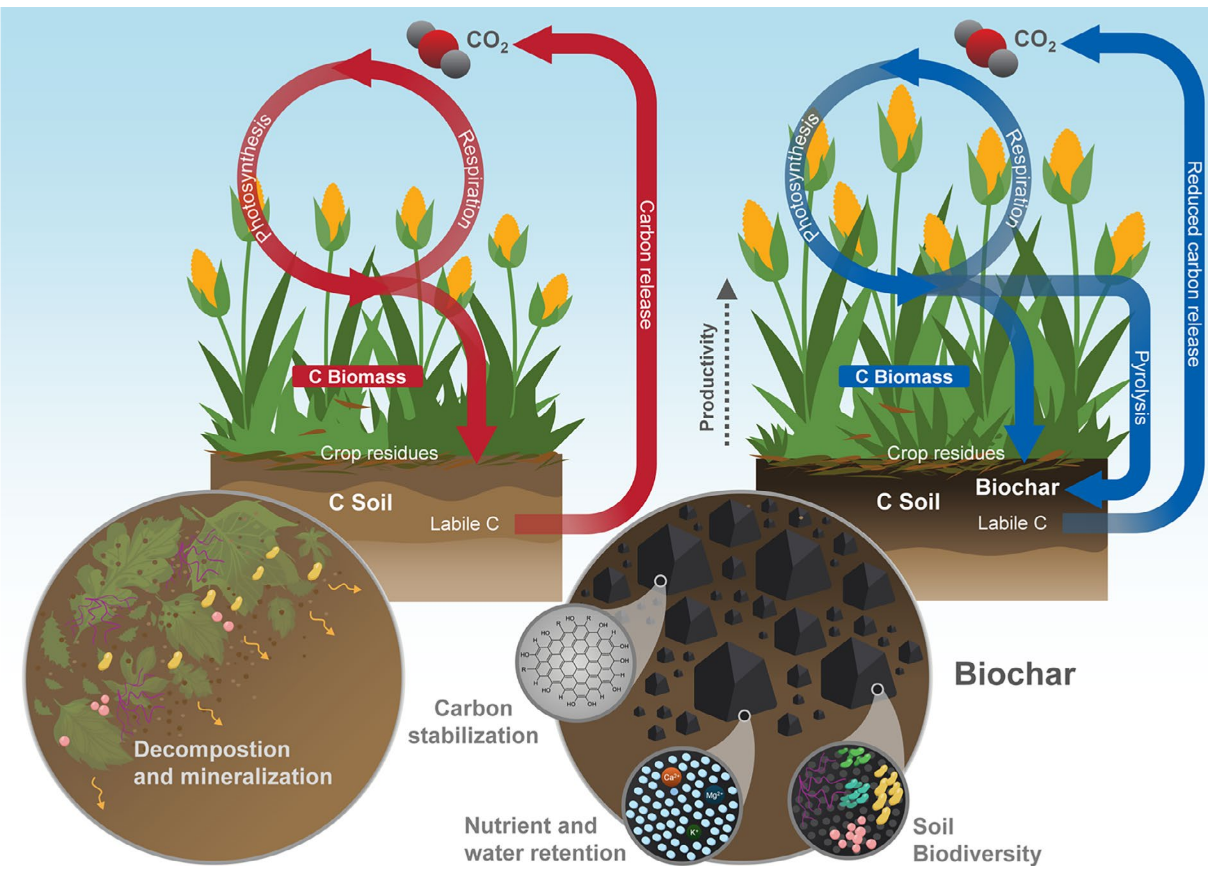

FIGURE 1 | Conceptual perspective on the carbon cycle and benefits of biochar application in soil.

Biogeochemical models such as the Rothamsted carbon model (RothC) (Coleman et al. 1997), the Environmental Policy Integrated Climate (EPIC) model (Williams et al. 1995), the Century Model (Parton et al. 1994), DayCent (Del Grosso et al. 2005; Parton et al. 1998), and DeNitrification-DeComposition (DNDC) (Li et al. 1992a, 1992b) play a crucial role in long-term simulation of soil C dynamics. They provide a reliable estimate and cost-effective approach to address complex interactions within soil, plant, and environmental dynamics, offering efficiency in both cost and time (Jiang et al. 2023). The use of models is already being considered by some certifiers for the commercialization of C credits, such as Approach 1 (Measure and Model) (Davoudabadi et al. 2023). However, these models face limitations due to the lack of extensive feedback and validation data on detailed spatial and temporal C patterns, primarily stemming from challenges in soil C monitoring (Dwivedi et al. 2023).

The extended time frame required to evaluate changes in soil C stocks can be considered an obstacle. Biogeochemical models offer an important approach to comprehending the drivers of long-term soil C dynamics and provide an opportunity to determine whether biochar addition to agricultural soil can yield positive impacts (Oelbermann et al. 2023). Currently, biogeochemical models incorporating biochar are still relatively scarce. Here, we provide a concise overview of biogeochemical models used to simulate soil C stocks with biochar input. The primary objective of this study was to conduct a literature review to identify key findings from relevant studies and identify critical research gaps. This review will guide future research directions by highlighting areas where further investigation is needed to explore the underlying mechanisms governing biochar–soil interactions and their impact on simulation models.

2 | Materials and Methods

2.1 | Data Collection and Processing

This bibliometric analysis was performed using the Web of Science (WoS) (Clarivate Analytics) platform. The search considered terms mentioned in the "title, abstract, and keywords" (Topic field) of each record and was limited to research articles published between 2000 and 2024. Figure 2 showed the retrieval terms used were: *Filter 1*: TS = ((Biochar) AND (biogeochemical models OR model OR simulation) AND (soil organic matter OR carbon sequestration OR carbon stocks OR carbon OR soil carbon stock OR carbon soil)). *Filter 2*: TS = ((Biochar) AND (soil) AND (biogeochemical models OR model OR simulation) AND (soil organic matter OR carbon sequestration OR carbon stocks OR carbon OR soil carbon stock OR carbon soil)). *Filter 3*: TS = ((Biochar) AND (biogeochemical models OR model OR simulation) AND (soil carbon stock)). *Filter 4*: TS = ((Biochar) AND (biogeochemical models OR model OR simulation) AND (soil carbon stock) AND (tropical soil)).

Here, "TS" denotes the "theme subject" search within the WoS database. Utilizing keywords, the TS retrieval technique employs Boolean logic to efficiently locate a significant volume of literature pertinent to the topic (Mongeon and Paul-Hus 2016). The data extracted underwent three main stages of processing: removal of duplicate entries, elimination of

FIGURE 2 | Retrieval terms.

irrelevant items, and consolidation of synonymous terms (Waltman et al. 2010).

2.2 | Bibliometric Review

The results from filter 3 were analyzed using the “Analyzing Results” tool from the WoS. The VOSviewer software was used to generate bibliometric maps based on the co-occurrence of the keywords, authors, citations, and other data (Waltman et al. 2010). The results were presented through graphics, and the most relevant works were explored in greater detail.

3 | Results

3.1 | Co-Occurrence Analysis of the Keywords

The application of the three query strings (Filters 1, 2, 3 and 4) resulted in 4259, 1238, 46, and 2 documents, respectively (Table S1). By analyzing the co-occurrence of keywords in relevant research papers, we can explore emerging research trends and identify future directions for biogeochemical models that account for biochar incorporation into the soil.

Considering occurrences of two keywords, the co-occurrence map indicates the establishment of eight clusters (Figure 3A) based on research themes concerning biochar. These clusters can be identified as climate change, use in agriculture, C sequestration, C fluxes, use in soil, interactions, and applications. The importance of research on climate change is evident, as is the interdisciplinary nature of topics like C sequestration and different applications. When we expanded the occurrence of keywords to five, only four clusters were identified (Figure 3B): C sequestration, climate change, interactions, and use in soil. This map serves as a valuable tool for understanding research trends in biochar, illustrating the primary interactions among the most frequently used terms in this field and the established clusters, thereby emphasizing the most pertinent terms. Through network analysis, keywords form clusters, with the size of each circle determined by the weight of the corresponding item. A larger circle indicates a higher weight. Lines connecting items represent links, while the distance between two keywords reflects their relatedness regarding co-occurrence links.

As shown in Figure 3, the modeling does not appear in the identified clusters, as it has not been extensively explored. Biochar modeling has only recently gained significant attention, with the number of publications considerably lower than corresponding experimental studies until recent years. As demonstrated in the bibliometric map, most research related to “modeling” is linked to “biomarkers,” including the capacity of biochar to improve effects on soil microorganisms and “Anthrosols,” especially the fertile soils known as “Amazonian Dark Earth,” characterized by their darker color, higher nutrient content, and abundant charcoal and artifacts—which served as the inspiration for the initial biochar studies (Schmidt et al. 2023).

Although biogeochemical models offer a powerful means of evaluating the effects of biochar on soil C dynamics, their use remains limited (Zhao et al. 2022). Furthermore, according to our research, biogeochemical models that consider the incorporation of biochar into tropical soils are scarce. The search using Filter 4 returned only two results from academic research on biochar and dissolved organic C in contexts that were not related to modeling soil C stocks. This lack of studies in tropical soils may be related to the scarcity of initial data necessary for the development of new models and improvement of existing models.

3.2 | Overview of Biogeochemical Models of Soil Carbon Stock With Biochar Input

Ecosystem models based on biogeochemical processes are used to simulate how biotic variables interact over time and space to determine the rates of biogeochemical fluxes. They simulate the interplay of biological factors and environmental processes to predict the rates of C and nutrient cycling. These models provide valuable insights for decision-making on climate change, land use, and water resource management (Berardi et al. 2020).

A recurring challenge highlighted across these modeling studies is the limited availability of long-term field experiments, which hinders the robust calibration and validation of models. Most studies incorporating biochar simulations within biogeochemical models have utilized the RothC model. Figure 4 illustrates the temporal progression of biogeochemical models incorporating biochar representations. Biochar inputs have been simulated across a spectrum of biogeochemical models, and their incorporation is often concentrated in the most recalcitrant C pools. In the following sections, we delve deeper into specific examples employing the RothC, APSIM, EPIC, Century, and DNDC models.

3.2.1 | Rothamsted Carbon Model (RothC)

The RothC model stands out as one of the first multicompartmental models developed for estimating soil C (Coleman et al. 1997). Initially developed to model C turnover in arable soils, the RothC model has been successfully expanded and optimized for use in diverse ecosystems, including croplands, grasslands, and forests (Coleman et al. 1997; Smith et al. 1997; Farina et al. 2013; Francaviglia et al. 2012; Skjemstad et al. 2004). The RothC model categorizes soil organic carbon (SOC) into active and passive pools. Active pools consist of decomposable organic matter, whereas more resistant organic compounds predominate in the passive pool (Jebari et al. 2021). The process is based on a five-compartment model with monthly time steps (Jordon and Smith 2022; Jebari et al. 2021; Morais et al. 2019).

Woolf and Lehmann (2012) investigated the potential of biochar to increase SOC stocks using a modeling approach. The model, which is a modified version of RothC, simulates the impact of biochar application on soil C turnover. The case study examined a scenario in which 50% of the crop residue was removed from the field for biochar production, and after the biochar was applied in the cropland (Woolf and Lehmann 2012). The model predicted a significant increase in SOC stocks (30%–60%) over a 100-year simulation timeframe compared to using corn stover as the soil amendment (Woolf and Lehmann 2012). The model incorporates a priming effect, in which biochar enhances the decomposition

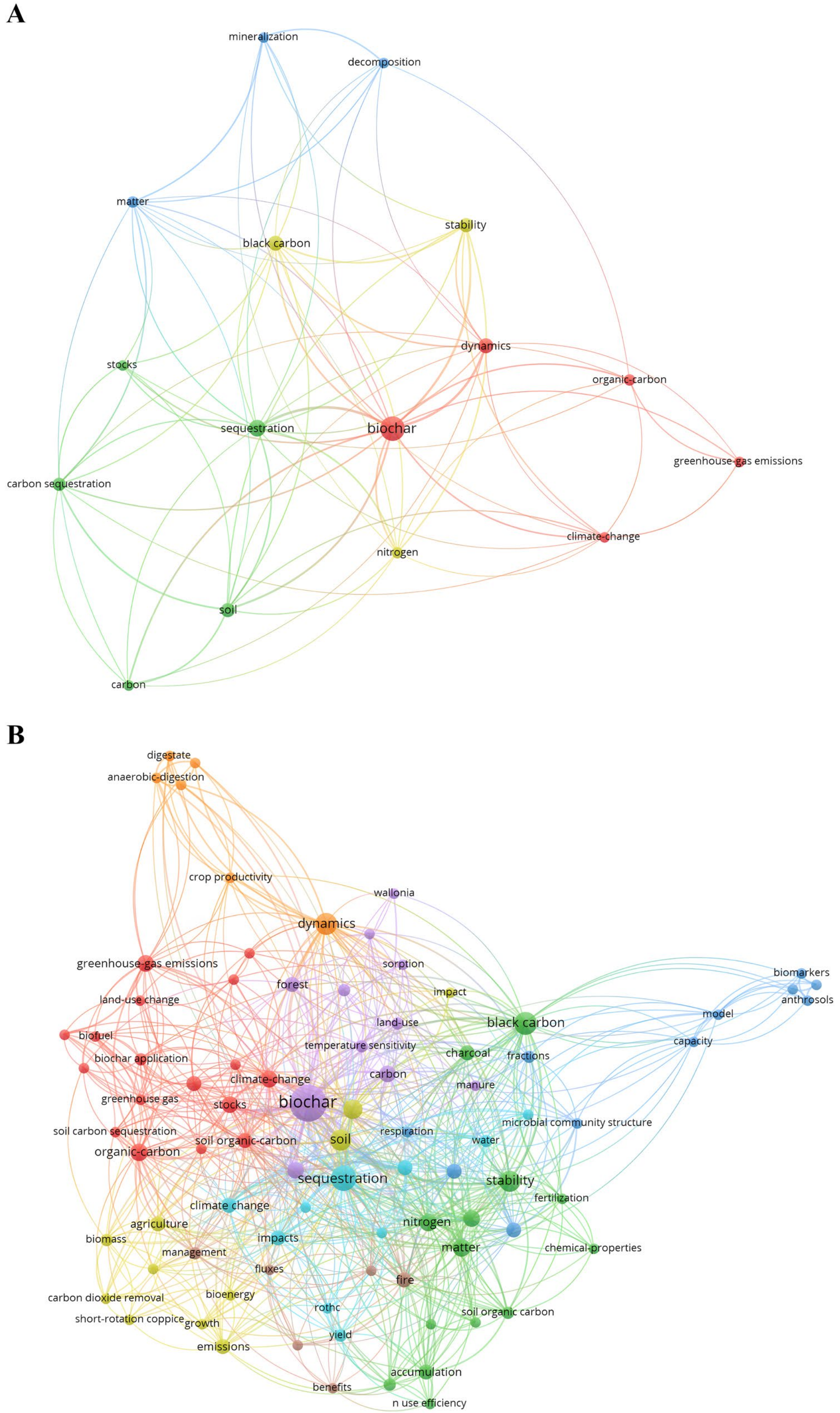

FIGURE 3 | Keyword co-occurrence map, where the size of each circle represents the weight of the corresponding item (larger circles indicate higher weight). Lines connecting the items represent links, and the distance between two keywords reflects their relationship in terms of co-occurrence. (A) Map showing the formation of eight clusters representing research themes related to biochar. (B) Expanded the occurrence of keywords for five main terms, identifying four clusters: Carbon sequestration, climate change, interactions, and use on soil.

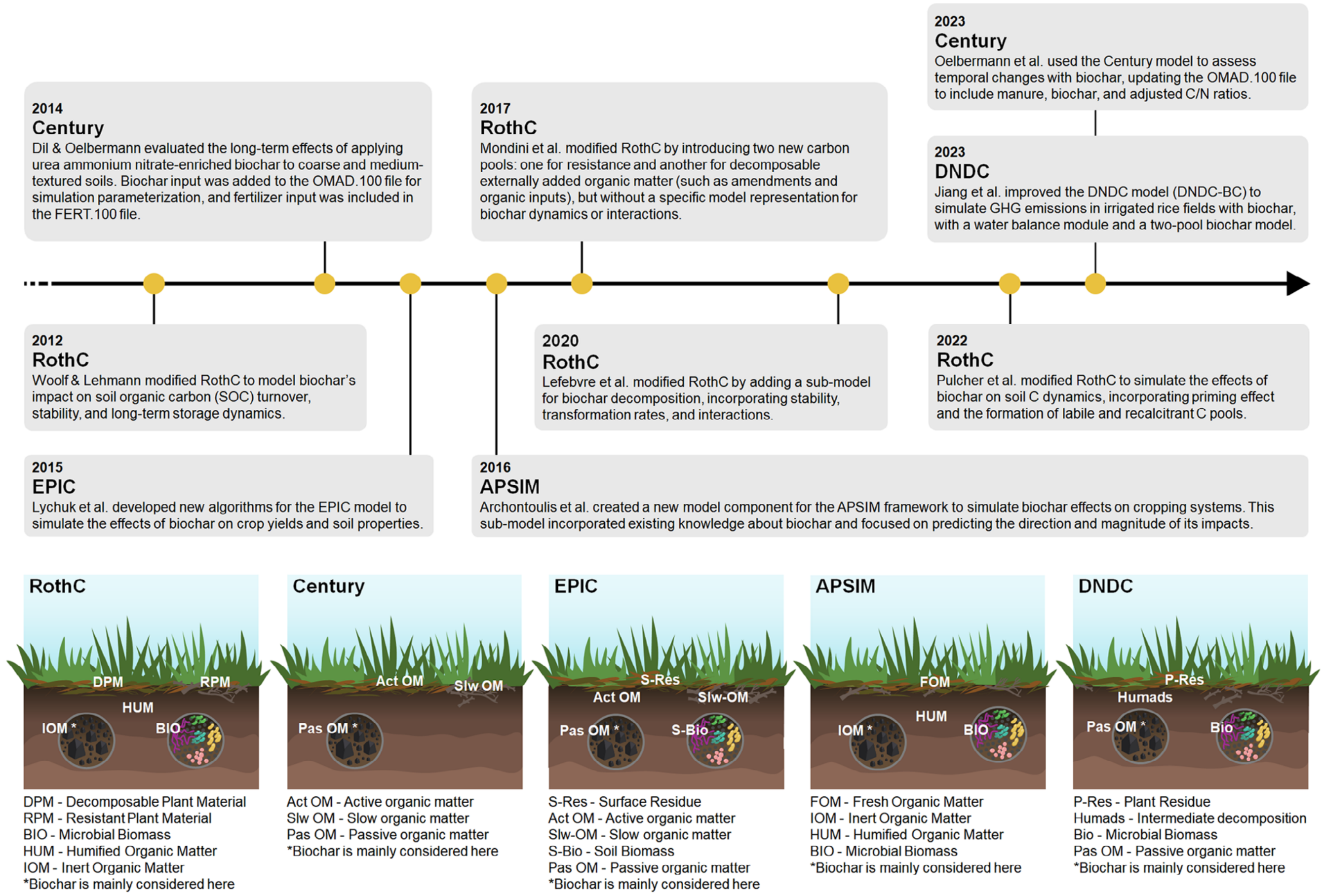

FIGURE 4 | Timeline of the biochar inclusion in biogeochemical models. At the bottom, it is listed how the soil organic matter compartments are included in each model.

of existing SOC. This was achieved by adjusting the decomposition rates within the model based on the biochar concentration in the soil. The authors acknowledge the limitations of the model, including uncertainties due to the scarcity of data on biochar priming effects and challenges in extrapolating from short-term laboratory studies to long-term field conditions. They emphasized that the model's primary value lies in its ability to identify how sensitive SOC stock predictions are to various parameters, providing valuable insights for future research. Although the absolute values predicted by the model may not be definitive, it offers a useful tool for understanding the potential benefits of biochar for soil C sequestration (Woolf and Lehmann 2012).

Mondini et al. (2017) have proposed incorporating various soil amendments, including green waste biochar, into the RothC model. This modified version of RothC introduced two new C pools: one for resistance and another for decomposable externally added organic matter, such as amendments, but without a specific model representation for biochar (Mondini et al. 2017).

Lefebvre et al. (2020) developed a modified version of the RothC model to evaluate the potential of sugarcane residues for producing biochar and sequestering C in the soil. The authors combined RothC with a submodel for biochar decomposition and considered the simulation to be satisfactory, highlighting the need for long-term field data to validate such simulations (Lefebvre et al. 2020).

Pulcher et al. (2022) conducted a long-term field experiment to investigate the decomposition of biochar in a poplar plantation in Italy. They modified the RothC model to simulate the effects of biochar on soil C dynamics, including its priming effect and the formation of labile and recalcitrant C pools. The model was validated by comparing its predictions with field measurements taken over 8 years. The researchers assumed that biochar C might not directly decompose into CO_2 but could instead be transferred to other C pools with varying decomposition rates. They also hypothesized that the rate at which biochar decomposes could be influenced by environmental factors like air temperature, soil moisture, and soil coverage.

3.2.2 | Agricultural Production Systems Simulator (APSIM)

The APSIM is a modular modeling framework developed by the Agricultural Production Systems Research Unit in Australia (Keating et al. 2023). APSIM was designed to simulate biophysical processes within farming systems. Its primary focus is on applications where economic and ecological outcomes of management practices are evaluated under climatic risk scenarios (Keating et al. 2023).

Archontoulis et al. (2016) created a new model component for the APSIM framework to simulate the effects of biochar on cropping systems. This submodel incorporated existing knowledge about biochar and focused on predicting the direction and magnitude of its impacts. While the model was developed based on literature information, it lacked specific calibration and validation using field data. The model simulates each soil layer independently. SOC is partitioned into three pools: microbial biomass (BIOM), humic matter (HUM), and inert organic matter (INERT). These pools exhibit different rates of decomposition. Fresh organic matter (FOM) is also divided into three pools based on decomposition rates. The model considers the different carbon-to-nitrogen ratios of BIOM and FOM, with BIOM having a fixed C:N ratio of 8 and FOM having a variable C:N ratio depending on its source (Archontoulis et al. 2016).

O'Brien et al. (2020) conducted a field study to assess the impact of different harvest intensities on CO_2 emissions from three continuous corn systems. The study evaluated three treatments: no tillage and no biochar, chisel plowing with biochar, and chisel plowing without biochar. CO_2 fluxes were quantified over a 3-year period (2010–2012). The APSIM model was calibrated using CO_2 flux measurements collected throughout the experiment. The calibrated APSIM model performed well in simulating CO_2 fluxes, soil temperature, volumetric water content, and stover removal. The model exhibited a slight bias towards underestimating the highest CO_2 emissions, which was primarily observed during the mid-growing season when root respiration was at its peak. However, these instances were infrequent, representing only 10% of the measured data. Overall, the model effectively simulated the observed trends in CO_2 emissions.

3.2.3 | Environmental Policy Integrated Climate (EPIC) Model

The EPIC model, initially designed by the USDA in the 1980s to evaluate erosion, has expanded its capabilities to simulate a wide range of agricultural processes, including crop growth, nutrient cycling, and water balance (Gassman et al. 2004; Longo et al. 2023; Williams et al. 1995). The EPIC model categorizes SOC into three pools: microbial biomass, slow humus, and passive humus (Lychuk et al. 2015). A small fraction of biochar might decompose quickly, while the majority decompose slowly or very slowly, assuming that biochar is primarily composed of organic matter (Izaurralde et al. 2006).

Lychuk et al. (2015) developed new algorithms for the EPIC model to simulate the effects of biochar on crop yields and soil properties. These algorithms were based on the current understanding of biochar's impacts. The model was validated using field observations from an Amazonian Oxisol, demonstrating its ability to predict the impacts of biochar on short-term crop performance and soil characteristics, such as cation exchange capacity and pH (Lychuk et al. 2015).

3.2.4 | Century Model

The "Century Model of Soil Organic Matter," abbreviated as Century, was one of the first developed and has been widely used due to its consistency and ease of application in studies of SOC dynamics. Century is a dynamic model that represents the changes in SOC, and, additionally, N, P, and S in the topsoil layer (0 to 20 cm). The Century Model categorizes SOM into three pools with varying decomposition rates: active, slow, and passive. The SOM decomposition rates are influenced by environmental factors, such as temperature and soil moisture (Parton et al. 1994).

Dil and Oelbermann (2014) evaluated the long-term effects of applying urea ammonium nitrate-enriched biochar to coarse and medium-textured soils. Biochar input was added to the OMAD.100 file for simulation parameterization, and fertilizer input was added to the FERT.100 file. It is important to note that the simulations in this study were not designed as a standalone validation of the model. Due to the short duration of the field trial (< 5 years), the model's performance could not be fully assessed by directly comparing simulated and measured data.

Oelbermann et al. (2023) applied the Century model to assess the temporal changes of SOC in soils treated with various combinations of manure, nitrogen fertilizer, and biochar. The model was parameterized to incorporate the effects of manure and nitrogen fertilizer amendments on the soil. The OMAD.100 file was updated to include the appropriate amounts of manure and biochar, and the C/N ratios were adjusted. Measured data were compared with predicted data. The model's predictions were acceptable, with differences from measured values falling between +9% and −1.3%. However, the limited duration of the field study restricted the model's validation. The authors note that the model may underestimate SOC stocks due to its lack of consideration for biochar aging. Future research should explore the interactive effects of climate change, soil management practices, and biochar on SOC stocks.

It is worth noting that, to date, no studies have been found in the literature that describe the use of a submodel for biochar in the Daycent model. Daycent is the daily time-step version of the Century model (Parton et al. 1994), C and N fluxes between the atmosphere, vegetation, and soil (Del Grosso et al. 2005; Follett et al. 2001; Parton et al. 1998; Del Grosso et al. 2001). Future studies should address this gap by incorporating a biochar submodel into Daycent.

3.2.5 | DeNitrification-DeComposition (DNDC) Model

The DNDC model integrates denitrification and decomposition processes to simulate GHG emissions from agricultural soils. The model incorporates subroutines for various agricultural practices, including fertilization, manure application, irrigation, tillage, and crop rotation, to predict the turnover of SOM (Li 1996).

Jiang et al. (2023) enhanced the DNDC model to simulate GHG emissions from irrigated rice fields treated with biochar. The improved model incorporated biochar modeling and water balance equations. This new version, known as DNDC-BC, included two additional modules: a water balance module and a two-pool biochar model (Jiang et al. 2023). The DNDC-BC model was evaluated through a 2-year field experiment in China to assess its ability to simulate the impacts of biochar and irrigation on GHG emissions, SOC, and grain yield. The results showed that the DNDC-BC model demonstrated satisfactory performance in simulating the effects of biochar and irrigation on CH_4, N_2O, SOC, and grain yield (Jiang et al. 2023). The DNDC-BC model showed the great potential of biochar and irrigation management in reducing GHG, increasing soil C sequestration, increasing yield, and saving water (Jiang et al. 2023). However, the validation was limited by the availability of only 2 years of measured data and one compiled dataset (22 sets from the literature) (Jiang et al. 2023).

3.3 | Other Models With Biochar Input

In addition to the biogeochemical models used for assessing soil C stocks mentioned in the previous section, the literature review identified studies that included biochar in other mathematical models.

Yin et al. (2022) evaluated the incorporation of biochar into a biogeochemical field model and established a daily resolution simulator to assess the 5, 50, and 500-year C sequestration potential of soil–biochar–plant interactions. This study proposed that biochar sequesters C through three primary mechanisms: (i) direct C storage from the biochar C input, (i) reduced mineralization of native soil C, and (iii) increased plant productivity leading to greater C capture through photosynthesis.

The effects of biochar on soil water characteristics were investigated by Xing et al. (2021) at a one-dimensional scale. The performance of different infiltration models was compared, and a novel optimization algorithm was proposed to improve the modified van Genuchten model. Results showed that biochar addition significantly reduced cumulative infiltration rates, with a more significant reduction observed at higher biochar percentages. The Kostiakov model outperformed the Philip model in predicting cumulative infiltration. The study demonstrates the potential to replace SWRC measurements with a one-dimensional infiltration experiment using the improved genetic algorithm and modified van Genuchten model, offering a more efficient and time-saving approach (Xing et al. 2021).

Foereid et al. (2011) developed a biochar–soil model in Excel spreadsheets to simulate the movement and decomposition of biochar in soil. The model assumed that biochar comprises two fractions with varying decomposition rates and can be transported through the environment. The model's sensitivity to erosion rate, moisture, and temperature was tested over a century, revealing significant impacts. However, the model was insensitive to the long-term stability of the biochar fraction, suggesting that it persists over millennia. The researchers discuss the implications of the model and future research directions. They highlighted that erosion losses may be more important for biochar than for other types of soil C components, and the models may need to be modified to account for soil erosion. Additionally, the model does not explicitly capture variations in biochar quality. The authors proposed incorporating this aspect in future iterations of the model, contingent on data availability for parameterization.

Usowicz et al. (2020) studied the effects of biochar on soil thermal properties in field experiments conducted in China and Poland. The experimental data included information on biochar application rates, soil texture, mineral composition, bulk density, particle density, water content, air-filled porosity, and organic matter content. These data were used to validate and improve the predictive capabilities of three models of soil thermal properties. The biochar rates in the field experiments ranged from 4.5 to 40 $Mg\,ha^{-1}$, while the modeling study considered a wider range of rates, varying from 52 to 267 $Mg\,ha^{-1}$ (Usowicz et al. 2020).

The most accurate predictions of thermal conductivity and diffusivity were achieved when the statistical-physical model incorporated the geometric mean of native SOM and biochar, and reduced the quartz content in the sand fraction from 100% to 72% (Usowicz et al. 2020). The addition of biochar decreased the thermal diffusivity at comparable water contents. Furthermore, the maximum thermal diffusivity occurred at higher water content levels as biochar content increased. The increased thermal diffusivity resulting from biochar application can help to regulate soil temperature, a crucial factor in plant growth and soil processes (Usowicz et al. 2020).

4 | Opportunities and Challenges

Although numerous studies have examined short-term effects under controlled conditions, a substantial challenge remains in extrapolating laboratory findings to the complex dynamics of field-based biochar applications. The observed variations, notably in the speed of biochemical reactions, are often linked to soil disturbance and altered environmental variables. As highlighted by Ringsby and Maher (2025), current assessments of biochar persistence are hampered by a limited body of short-term studies, comprising fewer than 20 publications and typically spanning only 1 to 2 years of evaluation. Consequently, there is a heightened risk of committing an ecological fallacy where conclusions drawn from these restricted datasets fail to predict outcomes at individual biochar deployment sites accurately.

The monitoring of biochar effects on soil is still in its early stages and can be conducted through a variety of techniques, including soil analysis, field experiments, and mathematical modeling. However, the complexity of the processes involved and the lack of long-term data still limit the understanding of the underlying mechanisms. Although the demand for predictive models is growing, large-scale adoption is still limited by uncertainty about the accuracy of the estimates. The accuracy of estimates varies significantly depending on spatial and temporal scale, soil type, and climatic conditions. Furthermore, for biogeochemical models to accurately simulate biochar dynamics in soil, it is essential to incorporate the understanding that different biochar compositions exert distinct influences on SOC dynamics.

The main benefit of using models in studies of biogeochemical cycles is their ability to integrate multiple factors, making simulations more realistic and incorporating the inherent complexity of ecosystems. Thus, these models significantly contribute to our understanding of how soils function and their ability to adapt to different conditions.

Biogeochemical models are valuable tools to assist decision-makers and those interested in soil C storage. Although programs to encourage SOC sequestration are not new, several approaches to measurement, reporting, and verification (MRV) of SOC exist. MRV protocols for SOC may include repeated collection of soil samples, application of biogeochemical modeling, use of remote sensing technology, or even a combination of these approaches to capture changes in SOC stocks over time. Hybrid MRV approaches, which combine soil sampling with modeling, have been shown to be effective in quantifying the responses of changes in SOC stocks. Furthermore, modeling allows projects to operate on a much larger scale than would be practical if frequent field sampling is required, given the high costs associated with this type of annual monitoring (Mathers et al. 2023).

Therefore, it is important to develop, calibrate, and validate simulation models that allow for the incorporation of biochar into soil management strategies. This is crucial for estimating the increase in soil C storage in systems using biochar. Furthermore, it is necessary to calibrate and validate these models in a variety of soils, including tropical regions, as research in this area remains limited. In the long term, the combination of improved models, more accurate monitoring, and the growing demand for nature-based solutions is expected to drive the development and refinement of biogeochemical models that consider biochar input into the soil.

5 | Conclusions

Biochar has been proposed as a promising technology for soil C sequestration and climate change mitigation and has been validated by several scientific studies presented here. However, assessing the long-term soil C sequestration potential of biochar is challenging because of several factors, including:

1. Short observation periods: Most biochar experiments involve short-term laboratory incubations or greenhouse experiments. These limitations often result in a lack of adequate representation of biochar behavior over time and space.
2. Neglecting crop–climate interactions: Most biochar research focuses on short-term effects on soil properties in controlled environments, neglecting how biochar interacts with crops and climate over long periods.
3. Measurement limitations: Currently, ex situ laboratory methods are used for measuring C (organic or total) in soil, resulting in high sampling frequency and analysis costs.
4. Scarcity rather than model validation data: The models used to predict the impact of biochar on soil C sequestration lack sufficient data for validation because of the aforementioned challenges in monitoring soil C.

To overcome these challenges and improve our understanding of the long-term C sequestration potential of biochar, future studies should focus on conducting long-term field experiments to evaluate biochar performance under real-world conditions. Validation data are necessary to improve the models' accuracy in predicting the impacts of biochar on soil C sequestration. The development of improved methods for measuring soil C stock changes that can capture spatial and temporal variability is paramount for the adequate use of models. Further research into the interactions among biochar, crops, and climate under field conditions is needed to better understand the long-term effects on agricultural productivity and GHG emissions.

Addressing these challenges will lead to a more comprehensive understanding of biochar's potential as a long-term C sequestration strategy and support the development of effective policies at national (i.e., Nationally Determined Contribution) and international (Paris Agreement; Conference of the Parties) levels.

Author Contributions

Amanda Ronix: conceptualization, data curation, formal analysis, investigation, methodology, validation, writing – original draft, writing – review and editing. **Eduardo Carvalho da Silva Neto:** conceptualization, data curation, formal analysis, writing – original draft, writing – review and editing. **Carlos Eduardo Pellegrino Cerri:** conceptualization, funding acquisition, project administration, resources, writing – original draft, writing – review and editing. **Agnieszka Ewa Latawiec:** conceptualization, methodology, writing – original draft, writing – review and editing. **João Luís Nunes Carvalho:** conceptualization, resources, supervision, writing – original draft, writing – review and editing.

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Ethics Statement

The manuscript was approved by all authors for publication.

Consent

I would like to declare on behalf of my coauthors that the work described is original research that has not been published previously and is not under consideration for publication elsewhere.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The datasets that support the findings of this study are openly available in Zenodo at https://doi.org/10.5281/zenodo.15195580.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.