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Current developments in soil organic matter modeling and the expansion of model applications: a review

To cite this article: Eleanor E Campbell and Keith Paustian 2015 *Environ. Res. Lett.* **10** 123004

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OPEN ACCESS

RECEIVED
7 June 2015REVISED
18 November 2015ACCEPTED FOR PUBLICATION
25 November 2015PUBLISHED
23 December 2015

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Keywords: soil organic matter, soil organic matter modeling, soil organic matter model applications, climate change policy, review
Supplementary material for this article is available [online](#)

Abstract

Soil organic matter (SOM) is an important natural resource. It is fundamental to soil and ecosystem functions across a wide range of scales, from site-specific soil fertility and water holding capacity to global biogeochemical cycling. It is also a highly complex material that is sensitive to direct and indirect human impacts. In SOM research, simulation models play an important role by providing a mathematical framework to integrate, examine, and test the understanding of SOM dynamics. Simulation models of SOM are also increasingly used in more ‘applied’ settings to evaluate human impacts on ecosystem function, and to manage SOM for greenhouse gas mitigation, improved soil health, and sustainable use as a natural resource. Within this context, there is a need to maintain a robust connection between scientific developments in SOM modeling approaches and SOM model applications. This need forms the basis of this review. In this review we first provide an overview of SOM modeling, focusing on SOM theory, data-model integration, and model development as evidenced by a quantitative review of SOM literature. Second, we present the landscape of SOM model applications, focusing on examples in climate change policy. We conclude by discussing five areas of recent developments in SOM modeling including: (1) microbial roles in SOM stabilization; (2) modeling SOM saturation kinetics; (3) temperature controls on decomposition; (4) SOM dynamics in deep soil layers; and (5) SOM representation in earth system models. Our aim is to comprehensively connect SOM model development to its applications, revealing knowledge gaps in need of focused interdisciplinary attention and exposing pitfalls that, if avoided, can lead to best use of SOM models to support policy initiatives and sustainable land management solutions.

1. Introduction

Soil organic matter (SOM) is generated from the dynamic biotic and abiotic processing of plant and animal detritus, representing the balance of inputs versus losses via such pathways as mineralization and leaching. In most soils, SOM is only a small percentage of soil mass, for example ranging from lows of <1% to highs of 8% to 9% in mineral soils under agricultural use (Davidson and Ackerman 1993, Haynes and Naidu 1998). However, SOM impacts many soil and ecosystem processes, including soil fertility, soil physical structure (Tisdall and Oades 1982, Six *et al* 2004), water infiltration, water holding capacity (Doran and Parkin 1994, Hudson 1994), and atmospheric

greenhouse gas (GHG) emissions (Heimann and Reichstein 2008). SOM is fundamental to many soil and ecosystem functions across a wide range of scales. It is also sensitive to the direct and indirect human impacts, e.g. through agricultural management practices (Matson *et al* 1997, West and Marland 2002), land use changes (Post and Kwon 2000), and shifts in nitrogen deposition and precipitation patterns (Schlesinger and Andrews 2000, Esser *et al* 2011). SOM’s quantity, quality, and dynamics can be used an indicator of human impacts on a wide array of ecosystem functions (Tiessen *et al* 1994), as well as a mechanism to improve soil health and its sustainable use as a natural resource (Elliott and Coleman 1988, Lal 2004).

SOM is challenging to bring into a single comprehensive analytical framework (Manzoni and Porporato 2009, Stockmann *et al* 2013). Direct measurements do not easily account for SOM's extreme physical, chemical, spatial, and temporal complexity (Dungait *et al* 2012), particularly using operationally defined (e.g., by mesh size, chemical extraction, density) measures of soil fractions with variable linkages to mechanisms affecting SOM dynamics (Wander 2004, von Lützow *et al* 2007). For decades, simulation models of SOM have therefore played a crucial role in research by providing an explicit mathematical framework to integrate hypotheses for soil processes, supporting hypothesis testing by predicting SOM dynamics across space and time. Their importance in SOM research is evidenced in citation records: on Web of Science, three of the five highest cited publications under the search phrase 'SOM' are model analyses³. However, SOM modeling approaches are diverse and continually evolving. Ideally, a SOM model would be based on mechanistic understanding of SOM dynamics, use SOM pools that can be informed by measured data, and be valid across multiple scales. At this point in time, however, no single SOM model yet fits this ideal. Indeed, inherent tradeoffs between model attributes (e.g., generality, predictive capacity, complexity) relative to their intended purpose suggest that no such ideal model can exist (Levins 1966, Sharpe 1990, Smith *et al* 1997).

SOM dynamics have become an increasingly important consideration in many areas of sustainability research and policy (Manlay *et al* 2007). These areas range from small-scale projects to preserve or improve soil health, to large-scale climate change mitigation strategies (Paustian *et al* 1998, Lal 2004, Karlen *et al* 2011, Powlson *et al* 2011). Direct SOM measurements alone do not easily support these types of efforts. Simulation models of SOM, however, provide the capacity for numeric evaluation of changes, including comparison of predicted impacts on SOM. This has led to an expanding use of SOM models in 'applied' settings, specifically to predict SOM dynamics in order to apply policy or to make decisions for how land is used (e.g. Taghizadeh-Toosi *et al* 2014). Considering the potential economic and policy implications of these model applications (carbon credits, for example, or payments for changing land management practices), there is an immediate need to better connect advances in SOM understanding with SOM model development and these rapidly expanding applications where SOM models are being used in decision making.

Here we review the state of recent SOM model developments and their connection to SOM model applications. We first provide an overview of SOM modeling, focusing on SOM theory, data-model integration,

and model development as evidenced by a quantitative review of SOM literature. Second, we present the landscape of SOM model applications, focusing on examples in climate change policy. We then conclude with a discussion of five areas of recent developments in SOM modeling, in order to examine their connection with SOM model applications in greater depth. These developments include (1) the role of microbes in SOM stabilization, (2) modeling SOM saturation kinetics, (3) temperature controls on decomposition, (4) SOM dynamics in deep soil layers, and finally (5) the representation of SOM in earth system models (ESMs). The aim of this review is to comprehensively connect SOM model development to its applications, revealing knowledge gaps in need of focused interdisciplinary attention and exposing pitfalls that, if avoided, can lead to best use of SOM models to support policy initiatives and sustainable land management solutions.

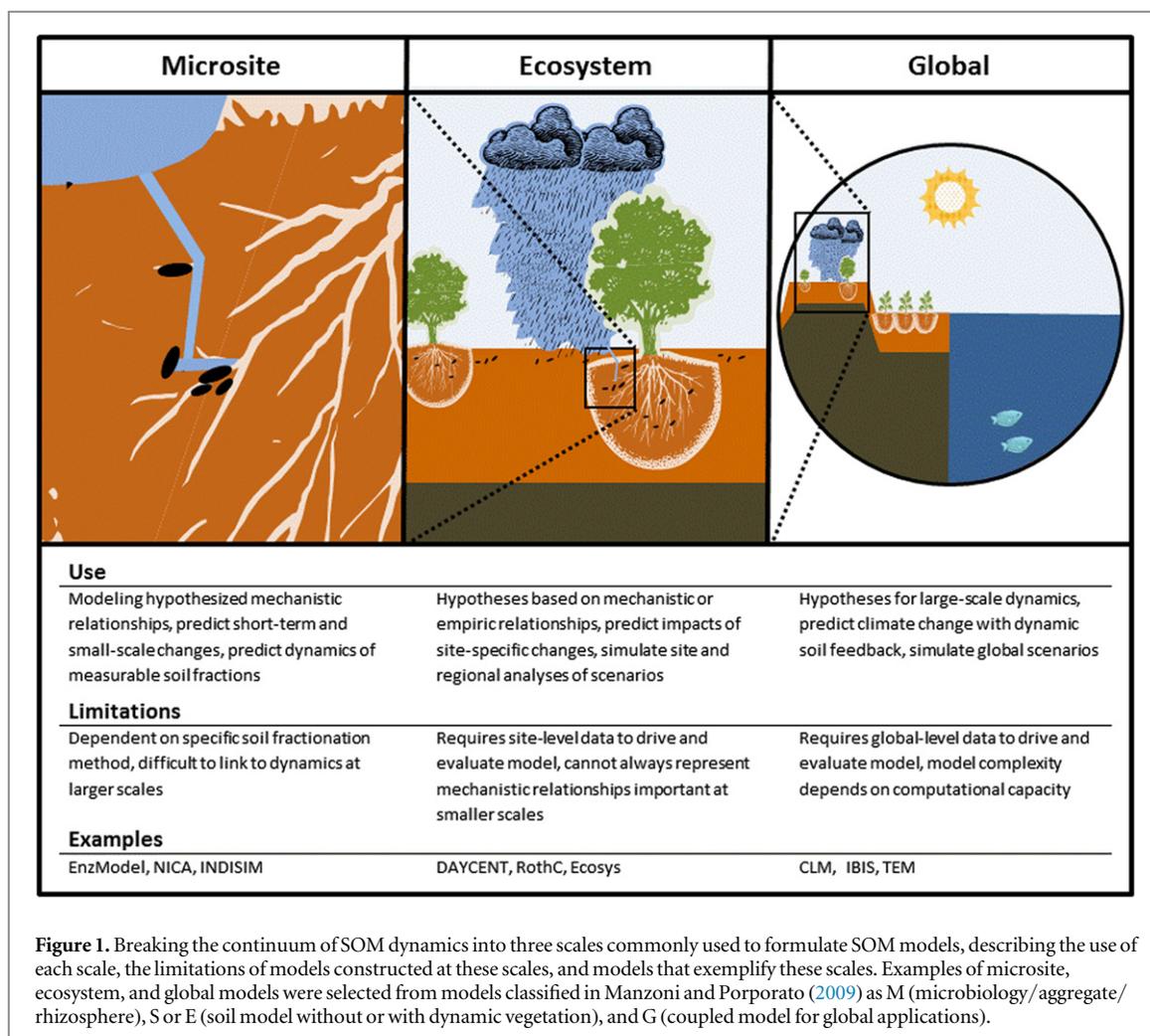
2. Overview of SOM modeling

2.1. Model theory and data-model integration

A model of a system must balance the conceptual understanding the model is intended to represent, the mathematical approach that best represents that understanding, and the data available to inform and evaluate how the model functions, within the constraints of available computational capacity. For SOM dynamics, the scale of model hypotheses and model uses require careful consideration, as different scales exert different types of limitations (figure 1). SOM models developed at one scale but used at another can lead to erroneous results (Manzoni and Porporato 2009), an area of concern in model applications driven by policy and land management decision making, where data to support model analyses may not be available at the scale of the decision being evaluated.

Across any scale, the 'toolbox' of mathematical approaches has seen relatively little recent expansion in SOM modeling. Rather, advancements are largely derived from new conceptual understanding of SOM dynamics (Parton *et al* 2015), although they are sometimes derived from the expansion of available data or improvements in computational systems. Many SOM models are formulated with multiple pools using first-order decay kinetics for mass loss. First-order decay is a modeling approach where the flux of material from a pool is linearly related to the quantity of material in that pool (example presented in figure 2). It is a mathematically (and therefore computationally) simple expression of decomposition using conceptual, kinetically-defined SOM pools that are not directly measurable *per se*, but have been proven through decades of testing as useful general approach (Paustian 1994), particularly over the long-term (e.g. Jenkinson and Rayner 1977, Parton 1987). Other emerging models define SOM pools based on specific stabilization mechanisms or as analytically measurable fractions

³ 'Soil organic matter' searched in the topic category 30 July, 2015. In order, the five highest cited publications were Walkley and Black (1934), Parton *et al* (1987), Sitch *et al* (2003), Potter *et al* (1993), and Batjes (1996).



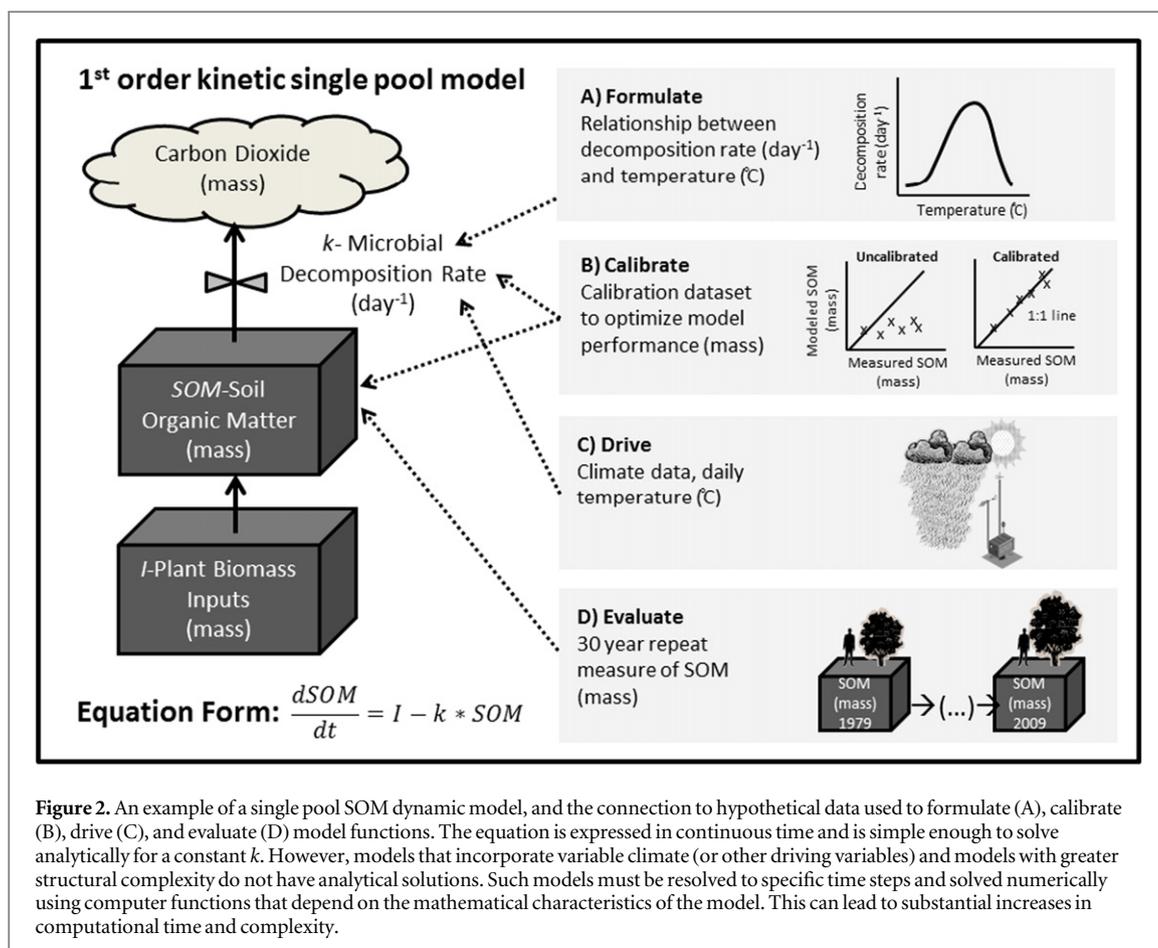
to better simulate short-term change (Tipping *et al* 2012, Segoli *et al* 2013, Davidson *et al* 2014).

A fundamental concern for any type of SOM modeling is the quality and quantity of available measured data to support modeling efforts. Other reviews have discussed the linkages between specific measurement methods and SOM model pools and dynamics (Wander 2004, von Lützwow *et al* 2007, Dungait *et al* 2012, Simpson and Simpson 2012). Here, we focus more generally on how data are integrated into different SOM model components.

There are several ways SOM models and SOM data interact. These can be grouped into four general categories: data to (1) *formulate*, (2) *calibrate*, (3) *drive*, and (4) *evaluate* a SOM model (figure 2). Data used to *formulate* SOM models are tied to the hypotheses that a model represents. An example: using incubation data from temperature-response experiments to mathematically define a SOM decomposition temperature response curve (e.g. Parton *et al* 1987, adapted in figure 2(A)). Data to *calibrate* a SOM model are used to parameterize components of an SOM model, optimizing model performance by ‘tuning’ parameter values to match observations when parameters are not measured directly (figure 2(B)). Data to *drive* a SOM model, on the other hand, are typically based on

external factors known or hypothesized to force SOM behavior. These data, depending on their scale and variation (e.g. soil texture or daily temperature and precipitation), can link spatial and temporal heterogeneity to simulated SOM dynamics (figure 2(C)). Finally, data to *evaluate* SOM models are used to validate model performance, evaluate uncertainty, and support hypothesis testing through the comparison of SOM simulations with measured results (figure 2(D)).

There are different potential pitfalls for model-data integration in each category. From the *formulation* side, data link to the hypotheses mathematically represented by a model. New data may prompt model changes, for example if new data alter the shape of an empirical relationship, or if new measurement methods yield new hypotheses for SOM processes. Data for model *calibration* act as a reference for the underlying modeled system, determining the extent to which the then calibrated SOM model can be used to test hypotheses and project across scales. Data for *drivers*, on the other hand, affect how spatial and temporal heterogeneity—e.g. in climate, soil texture—are represented. In either case, these components of SOM model analyses are sensitive to data limitations. Ideally *calibration* and *driving* data match the scale of the model simulation (i.e. as presented in figure 1), with fine resolution



for microsite-scaled model simulation up to broad coverage for a global-scaled model analyses. However, data limitations may necessitate the use of data of coarser resolution, for example, or mixing data of varying quality from varying sources. Model results are based on the assumption that calibration and driving datasets are reasonable reflections of true conditions, and are biased if this assumption is violated. Model *evaluation* entails similar limitations determined by the scale at which an SOM model is being used (Falloon *et al* 2002). However, data availability for model *evaluation* will affect assessment of model accuracy, as well as its ability to support hypothesis testing.

The suite of datasets for model formulation, calibration, driving, and evaluation yield different sources of uncertainty in SOM model predictions (Keenan *et al* 2011, Palosuo *et al* 2012). Suites of datasets are also often difficult to identify or compare between SOM models, particularly in large-scale ecosystem or global analyses. This is an area with the potential for rapid improvement, given advances in networks for model-data integration. For example, model research could connect to data management systems (e.g. Del Grosso *et al* 2013, Laney *et al* 2015), linking experimental data collection, analysis and curation (e.g. Michener *et al* 2011) directly to model integration and synthesis. Expanded datasets for model development, benchmarking, and multi-model comparisons (e.g. Luo

et al 2012) could then help identify and target subsequent experimental work and data collection, in an iterative cycle of model development and experimental research. However, networks for data-model integration have been slow to develop, requiring new infrastructure, the establishment of data management standards, as well as widespread scientific engagement.

2.2. Citation history for SOM model development

Looking more broadly, what is the current state of model development in SOM research? We chose to approach this question with a quantitative review of scientific literature. We drew on previous reviews by Manzoni and Porporato (2009), Falloon and Smith (2000), and Stockmann *et al* (2013)⁴, yielding a final list of 221 model publications considered in our analysis (appendix, table A1).

⁴ Manzoni and Porporato (2009) compared modeling approaches for carbon and/or nitrogen cycling processes in soils across a broad range of temporal and spatial scales ($10^0 \rightarrow 10^4$ m, $10^0 \rightarrow 10^3$ days). The authors selected model publications with high citation history and/or novel approaches to modeling soil carbon and nitrogen dynamics. The model publications are presented in Manzoni and Porporato (2009), including subsequent publications on the same model if it included a sufficient level of change to warrant separate consideration. The reviews by Falloon and Smith (2000) and Stockmann *et al* (2013) present soil carbon models selected by the more general criteria of 'common use' or 'current modeling approaches', and included some model publications unique from those presented by Manzoni and Porporato (2009).

2.2.1. Quantitative literature review methods

We treated the list of model publications of Manzoni and Porporato (2009)—202 publications, of the 221 total—as a record of model *development* from 1933 to 2009, due to their selection criteria emphasizing impact and novelty of modeling approaches. We recorded the number of times each of these 202 model publications had been cited in the Web of Science (WoS) Core Collection (as of 27 to 28 July, 2015). Some alternative search methods were used where WoS cited references were incomplete (see appendix and supplemental data). Using total citation values, we then evaluated: (1) the number of new model publications across decades, (2) total citations per publication, and (3) average yearly citations per publication.

In order to evaluate SOM model *uses* in scientific literature we chose to focus on ‘named’ models, pulling all unique model names from the three reviews where SOM or soil carbon dynamics were explicitly included in the model’s foundational formulation⁵. This yielded a final list of 87 named models that we then searched for ⟨model name⟩ AND ‘soil’ AND ‘model’ on WoS, again in the Core Collection. The goal for this search was to yield citations that included that model name explicitly in the title, abstract, or key words, which we could then treat as an example of the model being used as a central component of that analysis. This resulted in paring the initial list of 87 models down to a final list of 74 model names that were effectively searchable. See appendix for discussion of the 13 model names that were too common to be searched effectively, and had to be excluded from subsequent analyses.

Finally, the top ten most cited of the 74 named models were searched with ⟨top ten highest cited model names, separated by OR⟩ AND ‘soil’ AND ‘models’ AND ‘⟨comparison NEAR/2 models⟩’, and then manually refined, to identify publications for multi-model comparison analyses involving widely used SOM models. The publications yielded by this search were further manually refined to a subset using the single highest cited named model. This subset was then evaluated for the number of models compared in each publication, the purpose of each analysis, temporal and spatial scales, and main results.

Full results for all analyses are reported in the supplemental data.

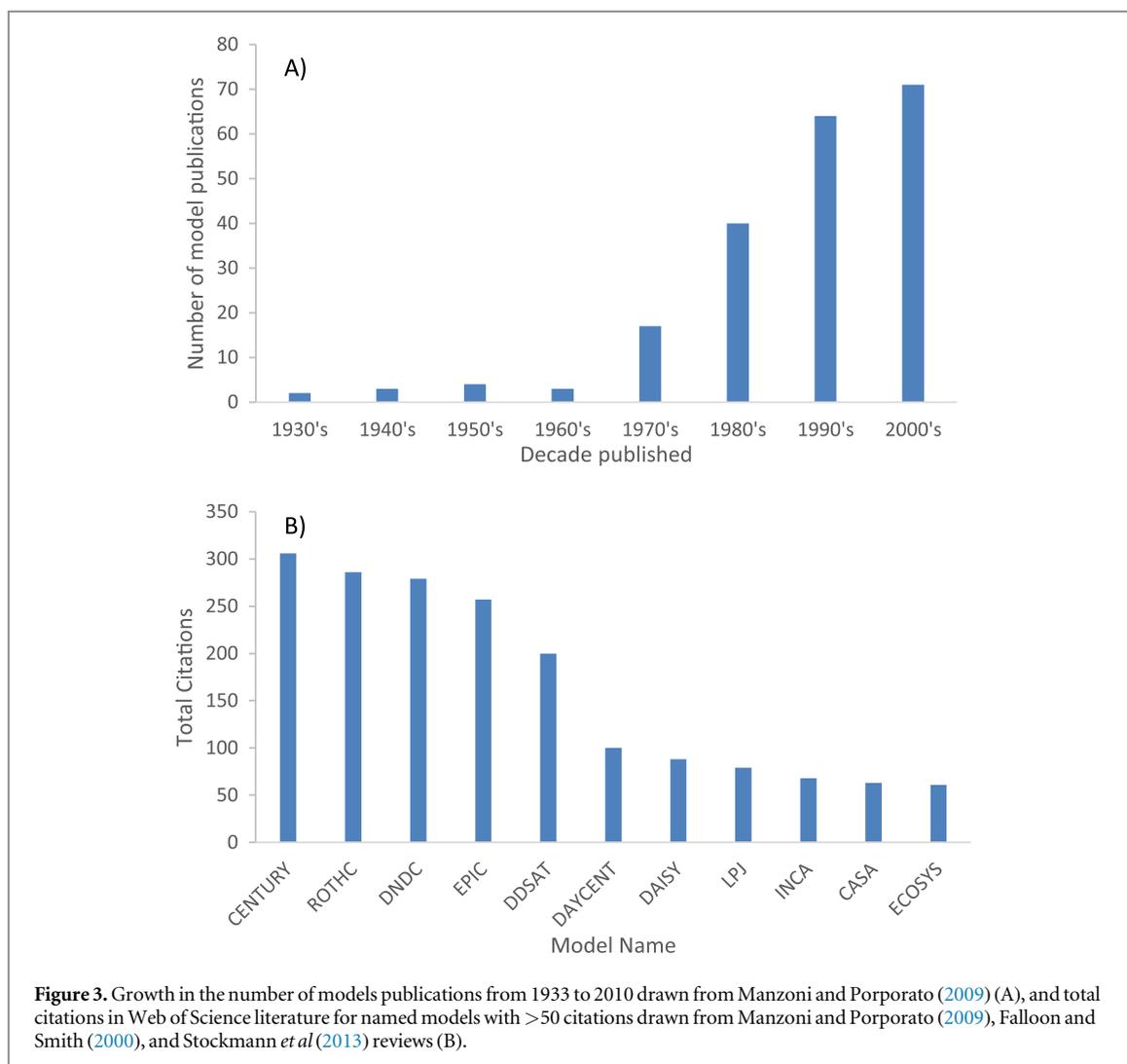
⁵ Foundational model formulations were evaluated in the first publication for each named model. We excluded named models that included *only* dynamic soil nitrogen in their foundational model formulation, but *not* soil carbon or SOM, as being less focused on broader SOM dynamics. The foundational publication of the APSIM model, for example, was reviewed by Manzoni and Porporato (2009) for simulating dynamic soil nitrogen. There are later versions of the APSIM model that do simulate dynamic soil organic carbon modeling and have been used in model analyses (e.g. Zhao *et al* 2013). However, APSIM publications are predominantly using the model for its initial purpose (crop modeling and nitrogen cycling).

2.2.2. Evidence for SOM development and use in scientific literature

The publishing years of the 202 model publications listed in Manzoni and Porporato (2009) provide evidence for continual development in SOM modeling approaches, extending back to the 1970s (figure 3(A)). However, while the number of SOM modeling approaches exhibits growth, there is evidence for strong influence from a small subset of key SOM model publications. For example, of the 202 model publications from Manzoni and Porporato (2009), the top ten most highly cited account for a disproportionate number of total citations, with only ~5% of publications representing 35.5% of total citations. CENTURY model publications outrank every other model, in three publications (Parton *et al* 1987, 1988, 1993) accounting for almost 11% of total citations. There is also some direct cross-over of model theories: approximately 10% (21) of the 202 models from Manzoni and Porporato (2009) were noted by the authors as being explicitly based on theory from prior publications. Of these 21 publications, almost half (10) cited theory from either CENTURY or RothC model publications. The remaining 11 cite theory from a variety of other sources (Verberne, DocMod, DNDC, NICA, TRACE, PHOENIX). The impact of key publications on SOM model development is further supported by the citations averaged across years since initial publication. Of the publications ranked top ten for yearly average citations, seven (including all three CENTURY model publications) were published before 1995, and all but one of these show consistent or increasing annual citations in recent years (appendix, figure A1).

Analysis of the 74 searchable ‘named’ models drawn from Manzoni and Porporato (2009), Falloon and Smith (2000), and Stockmann *et al* (2013) suggest that a relatively small subset of SOM models also dominate SOM model *uses* in the scientific literature (figure 3(B)). The model names that were ranked in the top five for citations account for 61% of total citations in this analysis. However, no single model clearly outdistances the others (figure 3(B)).

Multi-model comparison publications support a lack of consensus in SOM modeling approaches, particularly at the ‘ecosystem’ scale described in figure 1. A search for model comparisons including the top ten most cited named models (the first ten names in figure 3(B)) identified 34 multi-model comparison analyses published from 1995 to 2014. These multi-model comparisons showed an increase in frequency through time, with almost half (47%) of the 34 identified in this analysis published in just the last four years. The subset of these publications that include the highest cited named model (the CENTURY model, used in 8 of the 34 multi-model comparison publications) showed a dominant focus on multi-year time periods, and site- and regional-spatial scales. In all eight of the multi-model



comparisons that included CENTURY, there was no single model identified with conclusively higher performance. Rather, some models were shown to perform better than others for specific components or locations within the comparative analyses. One study suggested multi-model means perform better against measured data than any model individually (Palosuo *et al* 2012).

The results of this quantitative literature review show a dominance of a limited set of theories in SOM modeling approaches, alongside a great deal of uncertainty across scales. The latter is an important factor that continues to drive SOM model development, and that should be considered in SOM model applications.

3. The landscape of SOM model applications in policy

3.1. Connecting SOM models to policy instruments

There is ongoing expansion in the application of SOM models outside of academic research and linked more directly to policy. Historically, SOM models were one

component of scientific evidence (Oades 1984, Elliott and Coleman 1988, Paul and Robertson 1989) informing the types of land uses and soil management practices selected for policy support in agriculture. However, soil health, function, and productivity can connect to policies in fields as diverse as commodity production, urban growth, ecosystem services, and social justice. In these areas, SOM models can generate quantitative evaluations of SOM and ecosystem dynamics which can then be applied in decision making (e.g. van Ittersum *et al* 2008). The recent expansion of SOM model applications is therefore based in large part on their potential for direct roles in policy instruments (i.e., the tools a government or other organization uses to create change).

SOM models are appearing in policy instruments where the management of SOM is a component of policy goals, such as sequestering more carbon in soils as a climate change mitigation strategy (Stockmann *et al* 2013). SOM models are often one component of what Jasanoff (2003) calls 'predictive methods' (p 238), a general term for integrating scientific knowledge within a framework specific to policy needs. Predictive methods help simplify complexities at the interface of

Table 1. Policy instrument typology showing the theoretical connection, based on climate policy goals, between the type of policy instrument, the degree of obligation for action, and the use of predictive methods for GHG assessment.

Policy instrument type	Degree of obligation	Climate policy goal	Use of predictive methods for GHG assessment
Regulation	Policy obligates action	Change in GHG emissions required. Policy will support meeting GHG reduction and mitigation goals <i>directly</i> .	High certainty and credibility required. GHG emission values from predictive method are used to enforce policy.
Economic Incentives	Policy incentivizes action, encourages voluntary obligation	Change in GHG emissions encouraged. Policy <i>indirectly</i> supports GHG reduction and mitigation goals.	High certainty and credibility required. GHG emission values from predictive methods are used to allocate economic resources.
Information Programs	Policy does not obligate action	<i>No specific change</i> in GHG emissions encouraged. Policy does not support meeting specific GHG reduction or mitigation goals.	Uncertainty more acceptable. Information programs may support predictive method development for greater certainty. GHG emission values from predictive method have a range of uses, from policy development to education of target populations.

policy and science, particularly in the areas of natural resources and the environment⁶. However, as discussed in section 2, scientific development of SOM modeling is ongoing (figure 3(A)). New developments can easily be obscured or ignored in multi-faceted predictive methods for policy. This can lead, at best, to a lack of clarity in how a SOM model contributes to the results of a given predictive method, or, at worst, erroneous and misleading information.

A better connection is needed between ongoing advances in SOM research and SOM model applications in policy and decision making. Climate change policy is driving many recent developments in SOM model applications, and will be the focus of this component of our review. We base our selection of examples on expert knowledge in these types of SOM model applications.

3.2. SOM models in climate change policy

A common goal in climate change policy is to directly reduce or mitigate atmospheric GHG emissions. These efforts require applying scientific understanding of biogeochemical and ecological processes, a challenge both from the perspective of natural and physical scientists aiming to create ‘usable’ scientific knowledge (Dilling 2007, Logar and Conant 2007), as well as from the perspective of scientists and policy makers aiming to integrate scientific knowledge into better policy (Jasanoff and Wynne 1998, Jasanoff 2003, Sterner and Coria 2003, Brouwer and van Ittersum 2010). Land-based GHG emissions and soil carbon changes are important targets in policy instruments for GHG abatement, but are difficult to assess directly. This has led to widespread application of SOM model

simulations in ‘predictive methods’ for the GHG assessment of these areas (Bryan *et al* 2010, Gawel and Ludwig 2011, Stockmann *et al* 2013). Predictive methods are just one component of the complex economic, social, and political systems that shape policy. We therefore developed a basic policy instrument typology to categorize the use of GHG assessments in climate change policy (table 1), as a framework to explore specific examples of SOM model applications.

The policy instrument typology presented in table 1 drew from an approach discussed in *Carrots, Sticks, and Sermons* (Bemelmans-Videc *et al* 1998), using the following categories: regulation, economic policy, and information programs⁷. Developed from Etzioni’s classification of three kinds of power (Etzioni 1961), the typology is linked to the degree to which the government directly influences the governed—i.e., using regulation to require actions of the recipients (mandated obligation), using economic policy to encourage recipients to take action via material resources (self-selective, incentivized obligation), or using information to persuade recipients to take action (no obligation) (Bemelmans-Videc *et al* 1998). In table 1 we present the theoretical connection between the degree to which a policy instrument type obligates change, the contribution of that type of policy instrument to GHG reduction/mitigation targets, and the resulting requirements of predictive methods for GHG assessment.

We used this typology to examine the role of three types GHG assessments in which we identified examples of SOM model applications. These include: (1) GHG inventories, (2) carbon offsets, and (3) greenhouse house gas life cycle assessments. The conceptual

⁶ Predictive methods provide: ‘analysis of physical and social systems (that) hold(s) out the promise of understanding, and hence being able to manage, unimaginably complex phenomena through the prediction and control of salient variables’ (Jasanoff and Wynne 1998).

⁷ This typology combines the ‘resource’ and ‘minimalist’ approaches to policy typology, assuming that a government has already selected some policy goal and seeks to use its resources (i.e. policy instruments) to accomplish this goal.

framework presented here can be applied in other SOM model applications in policy instruments, for example including SOM management as a component of sustainability policy, or to policy based on valuation of ecosystem services. However, these areas of SOM model applications are less developed, and will be only mentioned in passing.

3.2.1. GHG inventories

GHG inventories aim to account for all GHG sources and sinks of an entity, ranging in scale from a single institution (e.g. a university, Klein-Banai and Theis 2013), to a nation (e.g. as required of parties to the United Nations Framework Convention on Climate Change (UNFCCC)). GHG inventories serve as a tool to comprehensively track the quantity and distribution of GHG emissions through time, either for information or for management of GHG emissions at an entity level. Their role within policy instruments tends to be either for *information programs* or for *regulation*, depending on the commitment of a given entity to reducing GHG emissions.

At large scales, land-based GHG emissions become an important component within GHG inventories. Evaluating land-based GHG emissions can require SOM model applications if high levels of spatial or temporal resolution are needed. For example, SOM model applications have emerged in national inventories (e.g. for the UNFCCC) constructed according to Tier 3 Intergovernmental Panel on Climate Change (IPCC) guidelines (Ogle *et al* 2013). The IPCC uses a three-tiered approach for GHG assessments, with basic data inputs and simple empirical models forming the basis of Tier 1 inventories while additional data and more sophisticated analyses are needed for Tier 2 and 3 inventories (Intergovernmental Panel on Climate Change 2006b). Tier 2 and 3 approaches are suggested by the IPCC for evaluating Key Categories, identified as ‘categories that have a significant influence on a country’s total inventory of GHGs in terms of the absolute level of emissions and removals, the trend in emissions and removals, or uncertainty in emissions and removals’ (Intergovernmental Panel on Climate Change 2006a, p 1.6). Agricultural systems and land use change are often key categories, in particular with the former a major source of nitrous oxide (N₂O) emissions, a powerful GHG (Forster *et al* 2007). Therefore, these are often areas targeted for higher tiered analytical approaches that require the use of SOM models for land-based GHG evaluation (US Environmental Protection Agency 2013).

IPCC methods for national GHG inventories provide an example of a rigorous standardized approach to GHG assessment, establishing best practices that encourage transparency, completeness, consistency, comparability, and accuracy (Eggleston *et al* 2006). IPCC methods also require uncertainty evaluations, with the expectation that areas of high uncertainty will

be targeted for future improvements (Eggleston *et al* 2006). This creates the potential for a mutually beneficial connection between GHG inventory assessments and SOM model research. Areas of uncertainty in GHG inventory assessments can identify SOM model shortfalls (Del Grosso *et al* 2006, Lugato *et al* 2010). Scientific development of SOM models can then be iterating across the standardized GHG assessment framework to generate improved GHG inventory assessments. We suggest that the use of SOM models within GHG inventories for entities at any scale should emulate IPCC methods.

3.2.2. Carbon offsets

Carbon offsets are a component of carbon markets that have emerged in wake of the Kyoto protocol and other climate policy initiatives where the primary target is *economic incentives*. Carbon offsets convert activities that reduce GHG emissions into priced commodities, aiming to harness market forces for climate change mitigation. Carbon offsets can be a component of either voluntary carbon markets (Kollmuss *et al* 2008) or compliance markets created to support mandated GHG reductions (e.g. the clean development mechanism for Kyoto Protocol GHG reduction targets). In either case, carbon offsets must be measurable and verifiable by independent third parties as well as meet criteria for additionality, permanence and leakage (Seeberg-Elverfeldt 2010b); i.e., they must be a demonstrable and long-lasting reduction in GHG emissions beyond what would have occurred under ‘business as usual’, and without causing increases in emissions elsewhere.

SOM dynamics can play an important role in carbon offset projects, particularly through agricultural management and land use change targeted to increase soil carbon sequestration. However, the complexity of SOM dynamics and the spatial variability of soil carbon stocks creates a challenge in meeting measurement and verifiability criteria. This challenge extends on both sides of carbon market transactions. Buyers are concerned with the quality and potential reversibility of these carbon offsets, while offset generators incur high costs to meet certification requirements. Soil carbon sequestration is currently excluded from the clean development mechanism for these reasons (Larson *et al* 2011).

Carbon offsets demand high certainty and credibility from GHG assessments (table 1). They do not easily accommodate complexity, variability, and scientific uncertainty in SOM dynamics. However, interest in bringing SOM management under the umbrella of carbon market valuation continues to be driven by its potential high value. Soils can also be managed for multiple sustainability criteria, supporting economic valuation for other ecosystem services (Powlson *et al* 2011). There is an emergence of land management-based GHG assessment standards in voluntary carbon markets (Seeberg-Elverfeldt 2010a). These

standards are often based on a hybrid combination of direct measurement and SOM model simulations. Under these approaches, direct measurements are used to support and/or verify results of SOM models applied to integrate interacting site-specific factors of a given project. The Verified Carbon Standard (VCS) and the American Carbon Registry (ACR) methodologies, for example, both include the use of models like CENTURY, DNDC, or APEX to evaluate baseline 'business as usual' emissions versus emissions under other management practices (Earth Partners 2012, Dell *et al* 2013). The VCS methodology recognizes the potential for model improvements, requiring new simulations if a new model version is used (Earth Partners 2012). The ACR requires extensive project-specific peer-reviewed model parameterization and validation, as well as proof of meeting criteria for model uncertainty standards (Dell *et al* 2013). In either case, carbon offset standards require the use of SOM models that have proven their applicability to the specific project being evaluated, requiring close engagement with experts in model use as well as the collection of sufficient data to accurately parameterize, drive, and evaluate the model. From the standpoint of SOM research, this suggests an opportunity for an ideal testbed of standardized data collection for model evaluation and development.

Carbon offset project reporting is already a component of carbon offset standards. We suggest project-specific measured data, meta-data, and SOM model simulation driver data should be made equally as accessible, allowing for more openly sourced use of these data for model testing. These data resources could contribute towards model development at the 'ecosystem' scale, which we recognized in section 2.2.2. as a particularly challenging scale for SOM modeling. Carbon markets would benefit by supporting SOM model development with improved model accuracy and quantified uncertainty, potentially expanding land-based GHG reductions that can generate carbon offsets.

3.2.3. GHG life cycle assessments

Life cycle assessment (LCA) is a framework used to quantify the impacts of a product 'from cradle to grave', i.e. from when a product is created to when it is disposed of or destroyed (Lee 2004). LCAs can be constructed to target any environmental aspect of a product, including GHG emissions, water impacts, or the use of nonrenewable material resources (e.g. Powers 2007, Cherubini 2010). They are a useful tool for informing policy and decision-making, by providing comparable numeric evaluation of production chains.

Conceptually, GHG-specific LCAs are similar in purpose to GHG inventories by accounting for all GHG emission sources and sinks. However, their focus is on products and production processes rather than entities. GHG LCAs are often needed when a

policy aims to change the carbon intensity of products, providing numeric evaluations for *information program* or *economic incentive* policy instruments. This is an area that has seen development in policy supporting alternative fuels as a climate change mitigation strategy. For example, in the United States the expanded renewable fuels standard (RFSII)—a component of the Energy Independence and Security Act of 2007—mandates the blending of increasing levels of renewable fuels, with an emphasis on cellulosic ethanol and 'advanced' fuels. In order to qualify, producers must use GHG life cycle assessments to demonstrate their fuels meet the RFSII requirement to reduce life-cycle GHG emissions by at least 20% compared to petroleum-based fuels (Congressional Research Service 2007).

Land-based GHG emissions become an important consideration when the product in question (or its production chain) impacts land use. This emerges for biofuels created from agricultural crops. Crop-based biofuels are tightly connected to land use concerns, particularly with their potential to conflict with food production (Cassman and Liska 2007, Tilman *et al* 2009). A series of publications also showed the potential for the expansion of bioenergy cropping systems to increase GHG emissions through direct and indirect land use change (Fargione *et al* 2008, Searchinger *et al* 2008). Consequently, policy supporting crop-based biofuels for climate change mitigation often requires accounting of land-based GHG emissions, a task well suited to SOM model applications⁸.

GHG LCAs are targeted towards shaping the decision making behind products and production chains. They can therefore be applied at a wide range of scales, and often are a component of multifaceted assessments that include net energy yields or other material impacts (e.g. water). The value of SOM models in these types of applications is to inform better land use decision making (Sheehan *et al* 2003). However, given the wide diversity of production systems (e.g. varying by scales, types of land use change, crop types), there may be limited data for model calibration and evaluation. For example, SOM model simulations may be coarser for a new type of land management, crop, or region, identifying where additional research or data collection would be valuable. Finer-scaled simulations, or model simulations with a higher level of certainty, may be needed to improve LCAs (Kwon *et al* 2013), for example to assess the incorporation of biofuels into a complex mosaic of multiple land uses to optimize environmental outcomes (Field *et al* 2016). Parallels can be drawn between LCA frameworks and the IPCC

⁸ For example, the main GHG assessment tool selected by the EPA to evaluate biofuel pathways for RFSII is the Greenhouse Gas, Regulated Emissions, and Energy Use in Transportation (GREET) model (IFC International 2009). SOM model simulations have been used to generate emission factors for GREET, as a way to evaluate soil impacts of bioenergy cropping systems (Kwon *et al* 2013, Ogle *et al* 2015).

best practices for GHG inventories, with the emphasis on transparency, acknowledgment of areas of uncertainty, and the creation of an analytical structure where improvements (in model performance or data availability) can be iterated through a LCA to improve accuracy. This is an area where collaborative data sharing and development of data-model networks would yield great benefits.

3.2.4. Conclusions for SOM models in policy

This section demonstrates that the connection between SOM research, SOM model development, and the applications of SOM models in policy depends on: (1) the policy-specific demands on SOM model applications, (2) tolerance for predictive uncertainty in model simulations, and (3) the ability of SOM models to meet these demands based on current understanding of SOM dynamics. SOM model applications in policy are best served by establishing infrastructure that links SOM model applications to the data used to formulate, calibrate, drive, and evaluate model simulations. This is important for transparency. It also creates a more direct connection between model improvements and support for better policy and decision making.

4. New directions in SOM model development

In this final section we review five areas of recent scientific developments in SOM modeling: microbial roles in SOM stabilization, SOM saturation kinetics, temperature controls on SOM dynamics, deep SOM dynamics, and modeling SOM in ESMs. We selected these five areas as both important to current SOM research and representative of a range of SOM development considerations (e.g. model complexity, scale, uncertainty, data availability). We reviewed each of these areas based on literature selected as representing main scientific developments and/or topics of controversy. Our aim was to connect developments in SOM modeling to specific challenges and considerations in SOM model applications.

4.1. Microbial role in SOM stabilization: why does SOM remain in soils, and for how long?

The persistence of OM in soils indicates operation of protective mechanisms that slow or prevent OM decomposition (Hedges *et al* 2000, Kleber 2010, Schmidt *et al* 2011). For example, some OM inputs are accessed quickly by soil microbes, mineralized within minutes, hours, or days. Organic matter that becomes protected from microbial activity, e.g. tightly bound to soil minerals within micro-aggregates or more temporarily stabilized within macro-aggregates (Tisdall and Oades 1982, Oades 1984, Golchin *et al* 1994, Six *et al* 2004, Pronk *et al* 2012, Six and Paustian 2014), can remain in soils for years, decades, centuries or

millennia (Oades 1988, Jastrow 1996). The net result of complex, interacting stabilization mechanisms is a mixture of organic residues, at different stages of decomposition and varying ages, that potentially react differently to change (Schimel *et al* 1994, Paul *et al* 1997, Trumbore 2000). This is a predominant SOM research area (Campbell *et al* 1967, Jenkinson and Rayner 1977, Parton *et al* 1987, Oades 1988) that has been subject to numerous reviews (table 2), as it is key to the role of soils in larger-scale processes (e.g. global carbon cycling), as well as their potential to either exacerbate or mitigate climate change (Schimel 1995, Jobbagy and Jackson 2000, Friedlingstein *et al* 2001).

Until recently, mechanisms for SOM stabilization were generally grouped into three categories: (1) physical protection from microbial processes (e.g. through aggregate formation), (2) mineral associations that limit exposure to lytic enzymes, and (3) increasing OM recalcitrance by selective preservation of less biodegradable litter inputs and the formation of complex, stable humic molecules (Sollins *et al* 1996, Six *et al* 2002, von Lützow 2008). Physical separation and mineral associations (categories (1) and (2)) continue to be recognized as important SOM stabilization mechanisms (table 2). However, the hypothesis that a large portion of SOM persists through gradual transformation of primary biomolecules into complex secondary 'humic' molecules resistant to decomposition (category (3)) has been challenged. Evidence supports the characterization of SOM as a complex mixture of smaller biopolymers distributed across the soil matrix, rather than as large complex humic molecules (Kelleher and Simpson 2006, Lehmann *et al* 2008, Piccolo 2002, Simpson *et al* 2007, Stockmann *et al* 2013, Sutton and Sposito 2005, von Lützow *et al* 2006, Wander 2004).

New hypotheses have emerged, centered on linking microbial processes with OM input chemistry and properties of the soil matrix (Schmidt *et al* 2011, Duggait *et al* 2012, Cotrufo *et al* 2013, Gleixner 2013). These hypotheses have invigorated a SOM modeling debate last visited in the late 1970s: to what degree should microbes and microbial mechanisms be explicitly represented in SOM simulations (i.e., making decay rates of SOM fractions a direct function of both microbial biomass and activity)? In the late 1970s, explicit microbially-based models such as PHOENIX (McGill *et al* 1981) and the model of Smith (1979) emerged alongside models using implicit microbial controls, such as the first 'Rothamsted model' of Jenkinson and Rayner (1977). At the time, research came down largely in favor of models employing simple decay kinetics without explicitly including microbial biomass, as those approaches were more successful modeling long-term SOM dynamics (Paustian 1994). However, currently implicit approaches to modeling microbes are criticized for not reflecting new hypotheses for SOM stabilization (Schmidt *et al* 2011).

Table 2. A selection of SOM reviews.

Publication	Title of review paper and description
Oades (1988)	'The retention of organic matter in soils'—clarifies terminology for soil carbon cycling and the linkage between the terms 'humus' and 'biomass'. Emphasis on physical stabilization and soil matrix interaction mechanisms that impact rates at which SOM is mineralized.
Sollins <i>et al</i> (1996)	'Stabilization and destabilization of soil organic matter: mechanisms and controls'—a conceptual framework for SOM dynamics aiming to bring together the state of the art in terms of mechanisms underlying SOM stability.
Falloon and Smith (2000)	'Modeling refractory soil organic matter'—review of soil organic matter models—including static, dynamic, single compartment, multi-compartment, and non-compartment approaches to modeling SOM with the longest turnover times.
Kuzyakov <i>et al</i> (2000)	'Review of mechanisms and quantification of priming effects'—consideration of SOM priming, and its potential to increase or slow SOM turnover rates. Additional: Fontaine <i>et al</i> (2007)—'Stability of organic carbon in deep soil layers controlled by fresh carbon supply'
Six <i>et al</i> (2002)	'Stabilization mechanisms of soil organic matter: Implications for C-saturation of soils'- evaluates mechanisms for SOM protection that have potential for saturation, proposing a fractionation method to evaluate soils for saturation kinetics.
von Lützwow <i>et al</i> (2006)	'Stabilization of organic matter in temperate soils: mechanisms and their relevance under different soil conditions—a review'—methodical discussion of all SOM stabilization mechanisms occurring in temperature soils, identifying uncertainties and inconsistencies. Questions inherent chemical recalcitrance as a stabilization mechanism.
Trumbore (2009)	'Radiocarbon and soil carbon dynamics'—a review of radiocarbon dating as an integrated measure of SOM cycling processes and turnover time over long-term timescales, centered on a state-factor approach to test hypotheses for SOM dynamics and showing differences in cycling dynamics across ecosystem components and timescales. Additional: Paul <i>et al</i> (1997)—'radiocarbon dating for determination of soil organic matter pool sizes and dynamics'.
Kleber (2010)	'What is recalcitrant soil organic matter'—complete examination of the term 'recalcitrant' in terms of general, mechanistic, and operational definitions. Examines logic for recalcitrance as a concept, arguing that it is largely semantic rather than providing meaningful connection to SOM dynamics.

Explicit microbial control of decomposition processes are also increasingly viewed as critical to simulate transient dynamics and adaptive responses by soil biota, both of which are important for predicting impacts from climate change (Lawrence *et al* 2009, Todd-Brown *et al* 2012). Simulating the quantity and/or longevity of SOM is frequently a primary objective for SOM model applications, making this a critical area for connection to new model developments.

Recent research on SOM chemical characteristics, interactions with microbial processes, and SOM persistence have generated new hypotheses and SOM modeling approaches (Ågren and Bosatta 1996, Rillig *et al* 2007, McGuire and Treseder 2010, Cotrufo *et al* 2013, Wieder *et al* 2013, Wieder *et al* 2014b). However, models reflecting these new hypotheses are largely theoretical and difficult to test in complex soil environments. It also remains difficult to determine whether explicit microbial mechanisms improve SOM predictions given the paucity of data to either drive or validate new models (Treseder *et al* 2012). This is an area where SOM research and applications would benefit by greater collaboration. Leveraging established model results and data testbeds within networks of long-term field experiments—*vis à vis* GRACenet/REAP (GHG reduction through agricultural carbon enhancement network/renewable energy assessment project) and the long term ecological research (LTER) network (Paustian *et al* 1995, Jawson *et al* 2005, Del Grosso *et al* 2013)—are examples of ideal testing

grounds for scaling up explicit microbial modeling to broader scales. Multi-model comparisons across spatial and temporal scales are also needed to determine if the added complexity of explicit microbial mechanisms leads to an improvement in SOM simulations.

It is unlikely that a single 'ideal' model will emerge from more explicit connections between microbial mechanisms and SOM persistence. The degree to which microbial mechanisms are integrated into SOM models will likely depend on the scale at which a given model is being used (Stockmann *et al* 2013). In SOM model applications, care should be taken to use a model most applicable to the scale of the system being evaluated.

4.2. SOM saturation: how much OM can soils hold?

Single and multi-pool 1st order decomposition kinetics are a relatively simple SOM modeling approach that performs reasonably well across a diversity of soils and land use changes (Paustian 1994). Mathematically, however, 1st order kinetics implies a *constant* maximum specific decay rate (i.e., '*k*' in figure 2) and thus a linear proportional relationship between OM inputs and the quantity of SOM storage when a soils system is at equilibrium (Stewart *et al* 2007). This is a reasonable mathematical approach for some theorized mechanisms of SOM stabilization (e.g. Kleber *et al* 2007). However, field and laboratory research suggest there is an upper limit, or 'saturation

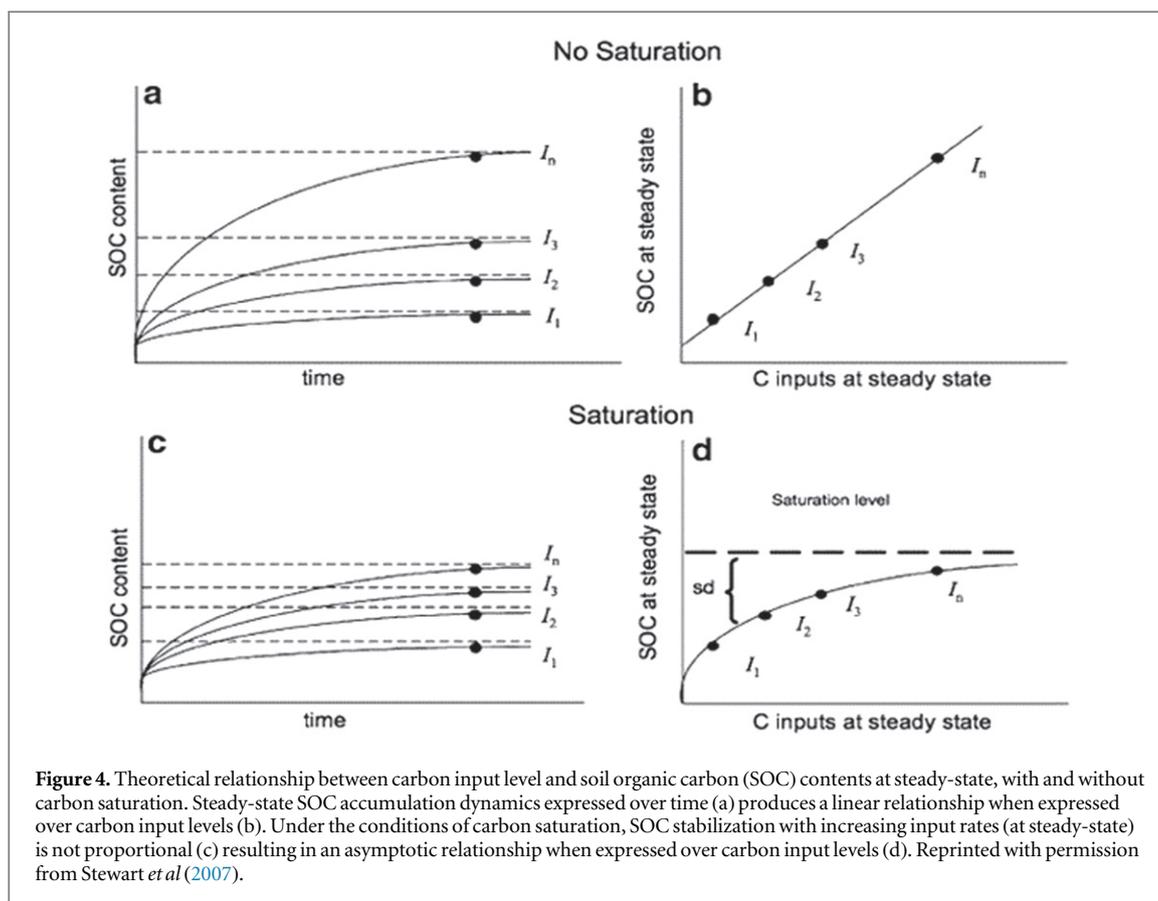


Figure 4. Theoretical relationship between carbon input level and soil organic carbon (SOC) contents at steady-state, with and without carbon saturation. Steady-state SOC accumulation dynamics expressed over time (a) produces a linear relationship when expressed over carbon input levels (b). Under the conditions of carbon saturation, SOC stabilization with increasing input rates (at steady-state) is not proportional (c) resulting in an asymptotic relationship when expressed over carbon input levels (d). Reprinted with permission from Stewart *et al* (2007).

level', in the amount of SOM that can be held in soil, determined by its physical characteristics⁹ (i.e., texture and mineralogy; Paustian *et al* 1997, Six *et al* 2002, Stewart *et al* 2007, Gulde *et al* 2008). Models based on 1st-order kinetics will therefore overestimate OM gains (e.g. due to increasing C inputs to soil) in soils that are approaching their saturation point (figure 4). This is an important consideration for SOM model applications in climate policy, given the potential to overestimate effects of land management intended to increase SOM storage.

Six *et al* (2002) defined three categories of SOM stabilization mechanisms; (1) mineral-associations (termed 'chemical protection'), (2) physical protection through aggregate compartmentalization, and (3) protection through inherent recalcitrance of SOM (termed 'biochemical protection'), with the remaining OM in the 'unprotected' pool. They linked these pools to measurable SOM fractions in order to evaluate the potential for saturation within each fraction and to link these mechanisms to a maximum capacity for total SOM protection (Six *et al* 2002). The 'biochemically protected' conceptual pool—i.e. complex, recalcitrant humic substances—have been largely dropped from studies evaluating saturation kinetics (following

⁹ If organo-mineral complexation is a predominant mechanism for SOM stabilization in soils (section 4.1), then it follows that the existence of a finite mineral surface-area would imply a finite amount of organic matter capable of being stabilized.

rationale from section 4.1). However, the potential for saturation kinetics to affect bulk SOM storage as well as dynamics between mineral-associated, aggregate protected, and unprotected SOM fractions have continued to be developed (Dungait *et al* 2012).

In experimental research, bulk soils have been evaluated to determine how close experimental soils are to their saturation capacity (Zhang *et al* 2010, Heitkamp *et al* 2012), with long-term studies suggesting a distinction between the absolute maximum capacity of soils to stabilize C versus a soil's 'effective stabilization capacity' given external factors such as disturbance by tillage (Balesdent *et al* 2000, Stewart *et al* 2007). Several studies used the Six *et al* (2002) framework to successfully evaluate soils for saturation behavior (Stewart *et al* 2008b, 2009). Other studies supported a hierarchy in SOM saturation, showing increasing OM inputs leading to SOM accumulation in labile, faster cycling fractions once mineral fractions were saturated (Gulde *et al* 2008, Castellano *et al* 2012). Concentration of SOM in the more labile pools due to saturation of more stable SOM pools are a concern for managing soils to increase SOM storage, as SOM in labile fractions are at greater risk for loss (Stewart *et al* 2012). One study suggested management practices to increase SOM storage should target soils with greater initial SOM deficits (Stewart *et al* 2008a), while another supported the need to intervene before soils reach a degradation threshold when stabilization mechanisms begin to decline (Kimetu *et al* 2009).

Saturation capacity for SOM is conceptually well defined, simple (on its own) to express mathematically, and increasingly supported by experimental evidence. It is notable, then, that saturation kinetics have not been widely invoked in SOM models, with only a few examples since the Six *et al* (2002) review (Malamoud *et al* 2009, Heitkamp *et al* 2012, Ahrens *et al* 2015). A key challenge in modeling SOM saturation is determining the maximum capacity for a given soil to store SOM. If a SOM model is based on measurable soil fractions, SOM maximum storage could be calculated based on soil chemistry or an empiric relationship observed at a specific site. However, for SOM models based on conceptually-defined SOM pools, maximum SOM storage is more difficult to link to measurable data.

Until SOM saturation kinetics can be appropriately implemented in SOM models, the potential for bias in SOM models based on kinetically-defined SOM pools should be recognized in SOM model applications aimed towards increasing SOM storage. High OM soils in systems with high OM inputs are vulnerable to overestimation of SOM storage and accumulation, when simulated using conventional first-order decay SOM models.

4.3. Temperature controls on SOM: Will temperature change make SOM increase or decrease?

Temperature is a key driver of SOM dynamics. This has been long established (Jenny 1941), and is not in dispute. However, in the last two decades debate has surrounded how SOM dynamics respond to temperature *change* (figure 5), motivated in part by the importance of understanding whether soils will become a stronger sink or source of CO₂ as temperatures increase under global climate change (Kirschbaum 1995, Trumbore *et al* 1996). Uncertainty in this area of SOM research is driven by the fact that temperature effects are difficult to isolate, and behaviors observed in controlled laboratory incubations are often less consistent and/or less discernible under more realistic *in situ* experiments¹⁰ (Kirschbaum 2000). At a micro-scale, for example, microbial decomposition processes are strongly affected by temperature in their immediate environment (Frey *et al* 2013, Hagerty *et al* 2014). However, microbial temperature responses at the ecosystem scale can be dynamic, if microbes acclimatize to varying temperatures or community characteristics change through time (Luo *et al* 2001, Allison *et al* 2010, Tucker *et al* 2013). The soil matrix and the chemical nature of the SOM substrate being decomposed can modulate temperature responses (Davidson and Janssens 2006). On longer timescales and at a landscape level, SOM responses can become

¹⁰ For example, in laboratory incubations temperature effects may be confounded by differential rates of labile SOM depletion (Conant *et al* 2010).

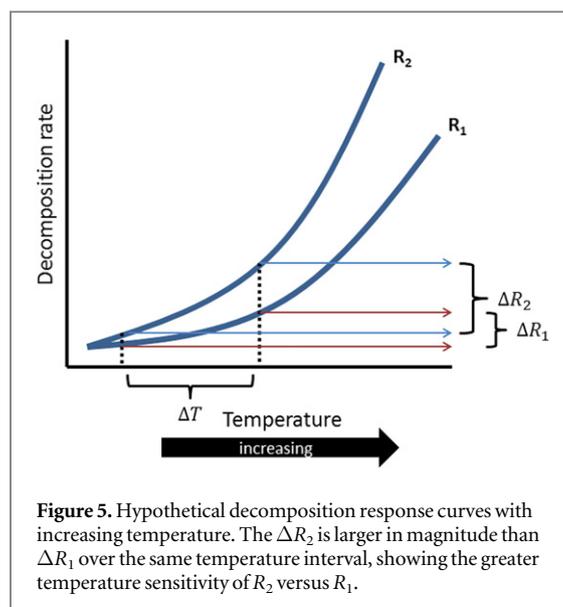


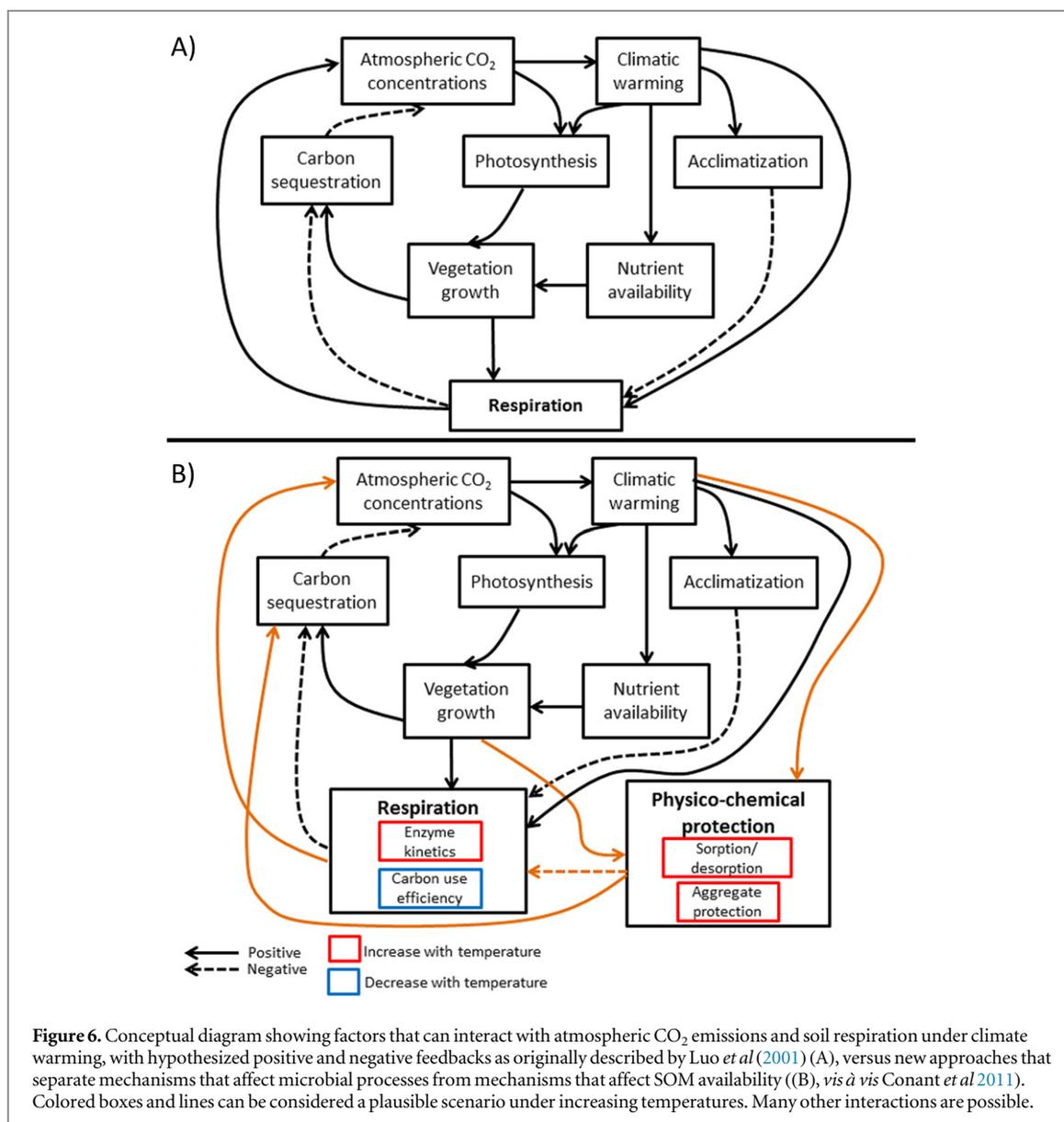
Figure 5. Hypothetical decomposition response curves with increasing temperature. The ΔR_2 is larger in magnitude than ΔR_1 over the same temperature interval, showing the greater temperature sensitivity of R_2 versus R_1 .

confounded with temperature effects on primary productivity (e.g. on photosynthesis, transpiration, vegetation structure, community dynamics) (Bardgett *et al* 2008). Ultimately, small-scale, isolated temperature responses and sensitivities in SOM dynamics may have a positive, negative, or no feedback with other ecosystem components in the soil environment when integrated over longer time scales, larger areas, or in interaction with other factors (figure 6).

This is an ideal area for SOM models to integrate and test hypotheses (Kirschbaum 1995, Jones *et al* 2003). Modeling approaches take the general form of defining a temperature response curve and associating it with a rate parameter that regulates SOM dynamics (e.g. figure 5). Differences in temperature sensitivity are reflected by either changing the shape of a temperature response curve (e.g. R_1 versus R_2 , figure 5), or having specific temperature response curves associated with specific SOM pools. There is no one universal mathematical expression of temperature response curves, although some have been shown superior to others¹¹ (Tuomi *et al* 2008).

Regardless of modeling approach, the mathematical expressions for temperature responses are linked to the underlying hypotheses for SOM structure (e.g. based on kinetically defined pools versus measured soil fractions). This creates the potential for wide variety in predictions of SOM responses to temperature change, leading to extensive debate. For example, one hypothesis proposed that ‘labile’ and ‘recalcitrant’

¹¹ Temperature responses are often exponential, so a common approach is Q_{10} , or a proportional change in respiration with 10 °C change in temperature. A Q_{10} of ~2 (i.e. a doubling of respiration with 10 °C temperature increase) is common across biologically meaningful temperatures, but Q_{10} values have been shown to differ substantially across soil fractions (Leifeld and Fuhrer 2005, Hamdi *et al* 2013). An Arrhenius type equation and a modified version referred to as the Lloyd and Taylor equation are other common approaches, connecting temperature effects to the activation energy of chemical reactions (Lloyd and Taylor 1994).



SOM fractions have different temperature sensitivities, with the latter being more sensitive than the former. This hypothesis was originally connected to a model now called the carbon quality-temperature theory (Fierer *et al* 2005), based on the concept that SOM decomposition dynamics were determined by substrate quality, via the number of enzymatic steps—and therefore the total free energy change—required to mineralize organic matter carbon¹². An argument against this theory suggested old SOM is less temperature sensitive than newer litter, leading to less carbon loss and even some carbon gain with increasing

¹² The carbon quality-temperature theory predicts greater temperature sensitivity in low quality substrates compared to high quality substrates, as well as greater temperature sensitivity at low temperatures versus high temperatures (Bosatta and Ågren 1999). Based on the assumption that 'old' SOM is more chemically complex and a poorer microbial substrate than 'new' SOM, this made a logical linkage to the hypothesis that 'older' (i.e. more stable, 'recalcitrant') SOM will be more sensitive to temperature than 'newer' (i.e. less stable, 'labile') SOM.

temperatures (Liski *et al* 1999). However, this argument was criticized for the assumption of fixed residence times in the pools used to model SOM and temperature effects on respiration (Ågren 2000). Subsequent studies have proved to be inconclusive for the temperature sensitivity of different SOM pools (Melillo *et al* 2002, Fang *et al* 2005, Conant *et al* 2008, Hartley and Ineson 2008, Benbi *et al* 2014), and a high level of uncertainty remains on this theory. However, it has been argued as largely irrelevant for mineral-associated SOM and SOM that is cycling more slowly (Kleber 2010, Conant *et al* 2011), as older SOM is not necessarily more thermodynamically stable or chemically different than 'newer' SOM (Kleber *et al* 2011).

This debate demonstrates the importance of the linkage between hypotheses for temperature responses on SOM dynamics and underlying SOM model formulations. For example, some widely used SOM models like CENTURY and DNDC may not directly reflect hypotheses for temperature-sensitive mechanisms

due to their basis on kinetically-defined SOM pools (Dungait *et al* 2012). Kinetically-based SOM models are commonly implemented in ESMs, often using Q_{10} functions to simulate temperature sensitivity (Todd-Brown *et al* 2013). This approach has been strongly criticized (Davidson *et al* 2006, Tang and Riley 2015), and shown to perform poorly simulating tropical and arctic ecosystems where climate change is of particular concern (e.g. Koven *et al* 2011). Researchers are beginning to explore more mechanistic approaches, based on understanding of factors such as substrate diffusion, enzyme activity, membrane transport, and microbial community dynamics (Grant *et al* 2003, Davidson *et al* 2006, 2012). Other recent models include mechanistic linkages to a wider array of SOM pools, for example differentiating between processes that make SOM available for decomposition (e.g. physical protection and aggregate turnover) versus processes that decompose SOM once it is available (e.g. microbial enzyme dynamics, depolymerization, figure 6) (Conant *et al* 2011). However, it is not yet clear if these modeling approaches lead to improved predictions at larger scales.

The impact of temperature change on SOM dynamics is likely to remain an area of SOM research with high uncertainty. For SOM model applications, this means care should be taken that the formulation of temperature responses in a given SOM model is empirically reflective of the system being assessed, even as the mechanistic understanding behind those responses are imprecisely understood. In systems where SOM model simulations perform poorly, temperature responses may be an area to consider models using different approaches. Greater standardization and clarity in how experimental data are reported and interpreted would support better integration with modeling efforts (Subke and Bahn 2010). Further experimental exploration of temperature-sensitive decomposition mechanisms—particularly including large-scale studies that cross a range of ecosystem types (Subke and Bahn 2010, Giardina *et al* 2014)—are needed to advance this area of research and better support SOM model applications where responses to temperature change are involved.

4.4. Deep soil dynamics: can subsurface soils be managed to store OM?

Soils can range in depth from a few centimeters to many meters. Our use of the term ‘deep soil’ refers to everything below the surface soil layer, which is typically considered to extend from 0 to 20 or 30 cm. Surface soils generally contain a large fraction of total SOM, in addition to SOM that is often younger, more rapidly cycling, more uniform (particularly in tilled agricultural soils), and more responsive to management perturbations than SOM in deeper soil layers (Scharpenseel *et al* 1989, Batjes 1996, Paul *et al* 1997, Jobbagy and Jackson 2000). Historically, SOM in

subsurface soil layers were thought to consist mainly of relatively inert humic material and mineral-bound OM. Consequently many SOM models only simulate dynamics in surface soil layers. However, while mineral-bound OM remains supported as a stabilization mechanism in subsurface soils (Rumpel and Kögel-Knabner 2010), more recent analyses show SOM in deeper layers to consist predominantly of highly processed microbial products (Erich *et al* 2012) that are responsive to land management change (Trumbore *et al* 1995, Baker *et al* 2007, Follett *et al* 2012, Poepflau and Don 2013), on shorter timescales than previously understood (Koarashi *et al* 2012). For example, Follett *et al* (2013) and Schmer *et al* (2014) have demonstrated in long-term field studies, that irrigation of previously non-irrigated sites result in a depletion of subsoil SOC and its associated SOM. Organic matter dynamics in the 50% or greater total SOM contained in soils below 20–30 cm has been identified as an important knowledge gap (Batjes 1996, Jobbagy and Jackson 2000), particularly in the context of subsurface soil responses to global change (Salomé *et al* 2010). Subsurface soils are now an important area of development in SOM modeling (Schmidt *et al* 2011).

Subsurface SOM dynamics involve similar mechanisms to surface soils, but with the potential for time lags and differences in soil environments that may separate subsurface and surface SOM responses to change (Fierer *et al* 2003a, Salomé *et al* 2010, Sanaullah *et al* 2011). A review by Rumpel and Kögel-Knabner (2010) provides a framework for recent experimental work focusing on subsurface SOM dynamics. They summarized key organic matter inputs to deeper soil layers as (1) the movement of dissolved organic matter (DOM) with water, (2) root growth, exudates, and turnover, and (3) physical OM transport through bioturbation or physical soil processes. Mechanisms that destabilize SOM in subsurface soils include aggregate disturbance and increases in microbial access to nutrients and labile carbon. Mechanisms that stabilize SOM in these layers are linked to mineral associations and the physical separation between dispersed microbes and SOM at depth. The relative importance of these factors is likely variable across ecosystems (Jobbagy and Jackson 2000, Schmidt *et al* 2011).

Experimental evidence for the interaction of stabilization and destabilization mechanisms in subsurface soils remains scarce, particularly from *in situ* field experiments (Rumpel and Kögel-Knabner 2010). Dissolved organic matter (DOM) is perhaps the best understood subsurface SOM input, known to cycle rapidly and play an important role linking surface OM with deep soil mineral fractions, SOM stabilization, and the potential for SOM long-term storage (Fröberg *et al* 2009, Rumpel and Kögel-Knabner 2010). The quantity and quality of DOM from different parts of the soil

profile can also serve as a metric for sorption, desorption, decomposition and leaching processes, as they interact with soil minerals, pH, litter, and hydrology (Kalbitz *et al* 2000). For any OM input, physical separation from microbes—as opposed to inherent OM chemical resistance to decomposition—has received widespread experimental support as an important stabilization mechanism (Rumpel and Kögel-Knabner 2010, Salomé *et al* 2010, Sanaullah *et al* 2011, Schimel *et al* 2011, Koarashi *et al* 2012). However, the mechanistic linkages between microbial community characteristics and subsurface SOM stability remain poorly understood (Fierer *et al* 2003a, 2003b, 2009, Kramer and Gleixner 2008, Eilers *et al* 2012). Evidence has shown that ‘priming’ is as an important destabilization mechanism, occurring when inputs of ‘fresh’ OM—i.e. labile OM that has not been microbially-processed—leads to increasing decomposition of otherwise persistent deep SOM with the stimulation of microbial activity (Kuzakov *et al* 2000, Fontaine *et al* 2007). Priming could play an important role in predicting subsurface soil responses to increasing concentrations of atmospheric CO₂, particularly in forested systems where elevated CO₂ has been shown to increase fine root production as well as cumulative carbon inputs into deeper soil layers (Iversen 2010). The potential for priming also must be considered in land management strategies for increasing SOM (Poeplau and Don 2013), particularly with the growth of deep-rooted crop species where priming may offset desired gains in SOM storage (Dungait *et al* 2012, Follett *et al* 2012). Research aimed towards evaluating priming in subsurface soils has not yet identified easily generalizable mechanisms, but rather suggests a high degree of site specificity (Langley *et al* 2009, Drake *et al* 2011, Iversen *et al* 2012).

Models of subsurface SOM dynamics are accordingly diverse and can be highly complex, particularly simulating multiple soil layers and dynamic movement of material between them (table 3). The Community Land Model (CLM), for example, was modified to simulate subsurface SOM dynamics using a vertical cascade approach, where SOM passes through layers in the soil profile with loss at each transition (Koven *et al* 2013). However, some models aim for simplicity; the DAYCENT model was modified to simulate deeper soil C dynamics by slowing SOM pool turnover and increasing allocation to passive soil C, without separating soil layers (Wieder *et al* 2014b), while the C-TOOL model took a practical approach by simplifying assumptions and solely focusing on whole-soil SOM dynamics in agricultural systems (Taghizadeh-Toosi *et al* 2014). Subsurface SOM models vary in explicitly or implicitly simulating DOM movement (table 3). Root inputs tend to show more consistency in mathematical approaches, often simulated using exponential functions (table 3), although one study argued for modifying models to

accept root distribution data directly (Iversen 2010). Bioturbation has been shown to be largely inconsequential compared to other input and transport mechanisms (Braakhekke *et al* 2013). Overall there is strong need for additional data to confirm or refute testable hypotheses suggested by different modeling approaches.

Recent research on subsurface SOM dynamics still only reveals pinpoints of understanding in a complex belowground system. Logistical challenges and lack of data are profoundly limiting. In this context, perhaps even more so than in other areas of SOM research, integration between experimental research and SOM model development is needed to advance understanding. For example, carbon isotope labeling and tracers are emerging as particularly important tools for subsurface SOM research, by allowing for OM dynamics to be observed with minimal disturbance. There is also likely value in using other, non-carbon tracers with known dynamics and interactions with SOM. For example, the use of ²¹⁰Pb_{ex} was able to inform SOMPROF model parameters, although use in addition with ¹⁴C or other carbon labeling was suggested as a more powerful approach (Braakhekke *et al* 2013). Given logistical challenges in studying subsurface soils, collaborative efforts between modelers and experimental researchers are needed identify, understand, evaluate, and predict SOM dynamics in soils below the 20–30 cm boundary that delineates much of our current understanding.

From the perspective of SOM model applications, this is an area of development that has the potential to add entirely new areas of consideration in predicting the SOM impacts of land management. It also could add the capacity to manage soils more effectively for long-term carbon storage, which is of high value in efforts to mitigate climate change. Policy efforts that involve SOM model applications could likely yield high value from supporting SOM data collection and model development efforts to better represent dynamics in subsurface soils.

4.5. SOM in global models: will soils contribute to or mitigate climate change?

As the largest terrestrial ecosystem carbon pool (Jobbagy and Jackson 2000), soils play an important role in determining global land-based carbon cycling and land-atmosphere carbon interactions. Models of SOM are accordingly needed in ESMs to dynamically link atmospheric carbon, climate change effects, and land-based carbon storage (Falloon and Smith 2000, Wieder *et al* 2014a). However, the inclusion of SOM models in ESMs present new challenges in SOM model development and validation, due to uncertainty, variability, and uneven coverage in data needed to drive and evaluate SOM model performance at such large scales.

Table 3. Comparison of a selection of SOM models simulating deep soil dynamics.

Model	Timestep, simulation timeframe	Depth	Drivers	SOM	Dissolved OM	Roots	Bioturbation
SOLVEG-II (Ota <i>et al</i> 2013)	0.25 h timestep, immediate to long-term simulations	5.5 m, 27 varying layer depths	Temperature, moisture, soil texture	1st order, CENTURY-type structure, 3 pools each layer (active, slow, passive)	<i>Explicit</i> , f(diffusion, advection, uptake, water flow, decomposition)	Exponential function across depth	NA
C-TOOL (Taghizadeh-Toosi <i>et al</i> 2014)	Monthly, medium to long-term simulations	100 cm, 0–25 cm and 25–100 cm	Temperature, clay content, soil C/N, OM inputs	1st-order, 3 pool	<i>Implicit</i>	Exponential function across depth	NA
SOMPROF (Braakhkke <i>et al</i> 2013)	Monthly, medium to long-term simulations	0.7–2 m, variable layer depths	Temperature, moisture	1st order, root and fragmented litter, leachable and non-leachable slow OM in mineral layer	<i>Implicit</i> , effective advection with liquid transport	1st order decay	Single rate, with diffusion transport
RothPC-1 (Jenkinson and Coleman 2008)	Monthly, medium to long-term simulations	92 cm: in 0–23, 23–46, 46–69, and 69–92 cm depth increments	Temperature, moisture, clay content	1st order, including microbial biomass, humus, and inert OM pools	<i>Implicit</i>	1st order decay, implicit in C flows through ‘decomposable’ versus ‘resistant’ plant OM pools	NA

Dynamic modeling of terrestrial carbon cycling in ESMs appeared in the 1990s, when the mechanistic representation of photosynthesis and stomatal conductance (e.g. implementing the model from Farquhar *et al* 1980) created a dynamic linkage between the atmospheric carbon cycle and terrestrial net primary productivity (NPP), allowing carbon movement to be simulated through other terrestrial ecosystem processes (Pitman 2003). For the sake of simplicity, initially ESMs simulated climate change effects on soils separately from climate forecasting models (Jenkinson *et al* 1991, Schimel *et al* 1994). Subsequent coupled atmospheric and terrestrial carbon cycling models predicted the potential for soils to accelerate climate change (Friedlingstein *et al* 2001), with the effects of increased CO₂ concentrations on photosynthesis being surpassed by temperature effects on soil respiration (Cox *et al* 2000). Following this, ESM simulations and multi-model comparisons included some form of SOM modeling, varying in the number of soil pools but generally using 1st order kinetics (Sitch *et al* 2003, Krinner *et al* 2005, Friedlingstein *et al* 2006). ESMs have since been developed to link carbon and nitrogen cycling, as well as the simulation of land use and land cover changes (LULCC) with climate change (Friedlingstein and Prentice 2010, Lawrence *et al* 2011, Wang *et al* 2013). More recently, ESMs have been developed to include soil carbon and nitrogen cycling in deeper soil layers (Koven *et al* 2013).

As ESMs advance and accommodate higher levels of computational complexity, there are opportunities to incorporate new approaches in SOM modeling. For example, microbial dynamics have direct and indirect linkages to land-atmosphere carbon exchange (Bardgett *et al* 2008, Allison *et al* 2010, He *et al* 2010), and the lack of explicit microbial processes in most ESMs has been criticized (Schimel 2013). Researchers argue that more mechanistic representations of microbial growth efficiency (Wieder *et al* 2013, Xu *et al* 2014) and microbial biomass would improve ESM predictions (Todd-Brown *et al* 2012, Fujita *et al* 2014). However, these efforts are hampered by model complexity and data availability. There are efforts to develop useful abstractions and simplifications of SOM dynamics (Wutzler and Reichstein 2013), as well as to use microbial enzyme kinetics and stoichiometric constraints to derive a 'first principles' approach to SOM dynamics that might emulate the early success of simulating photosynthesis and stomatal conductance in ESMs (Pitman 2003, Bonan *et al* 2012, Davidson *et al* 2014). Essentially, representing SOM dynamics in coupled global models requires determining how best to scale up in spatial resolution while scaling down and simplifying model processes as

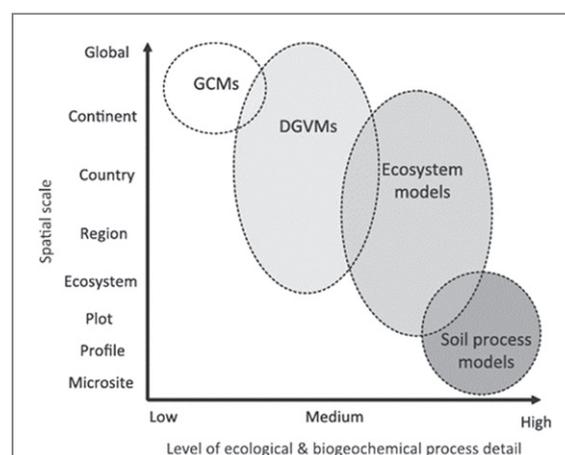


Figure 7. Conceptual grouping of carbon models across scales, in terms of process versus application, where GCMs refers to global circulation models (e.g. earth system models), and DGVMs refer to dynamic global vegetation models. Reprinted with permission from Ostle *et al* (2009).

much as is required (Arneth *et al* 2009, Ostle *et al* 2009, figure 7).

Multi-model comparisons of ESMs are needed to evaluate SOM modeling approaches, using validation datasets that range from regional to global scales. A number of ESM model comparisons, parameter validation, and benchmarking projects are ongoing (table 4) (Luo *et al* 2012), with organizations like the world climate research programme providing resources to support project development. Researchers have repeatedly recognized that development and application of ESMs is fundamentally an interdisciplinary effort (Bonan *et al* 2002, Pitman 2003). Given the importance of climate change prediction across temporal and spatial scales, alongside the increasing sophistication in developing and evaluating climate change scenarios for mitigation and adaptive measures (Moss *et al* 2010), we would like to emphasize the importance of this area of research and the need for collaboration between ESM researchers, SOM model developers, and SOM field and laboratory researchers alike to advance predictive abilities. Expanding the network of scientists involved in projects like the coupled model inter-comparison project (CMIP5) could lead to more rapid advances in understanding climate–soil interactions in the context of the global carbon cycle, in addition to supporting better predictions of future climate change.

In SOM model applications, this is an area of SOM model development likely most relevant for policies at regional and national scales. In particular, ESMs may help identify areas where SOM model performance is poor or biased in the context of observed OM patterns at large scales. This may help identify regions where SOM model applications need to be adjusted based on

Table 4. Selection of model intercomparison and model-data integration projects focused on carbon cycling and including a soils component.

Name	Description	Status and resources	Select contributions	Publications
International land model Benchmarking project (ILAMB)	Model-data integration and intercomparison; develop and promote benchmarks; software system for benchmarking	Ongoing, www.ilamb.org	Identify ecosystem benchmarks for measured/ modeled comparison, to reduce equifinality problem	(Luo <i>et al</i> 2012)
Project for intercomparison of land surface parameterization schemes (PILPS)	Land surface process modeling inter-comparison of parameters; community-based documentation, comparison, and validation of parameters	Designed to be on-going, listed as a former model intercomparison project by World Climate Research Programme, http://wcrp-climate.org/	Comparison of 1st versus 2nd generation models showed improvement when plant–soil interactions with atmosphere are dynamic, instead of passive; developing use of isotopes to improve parameterization	(Pitman 2003, Henderson-Sellers 2006)
Coupled carbon cycle climate model inter-comparison Project (C4MIP), now incorporated in the coupled model intercomparison project phase 5 (CMIP5)	Isolate feedback between the carbon cycle and the climate in the presence of external forcing	Ongoing, http://c4mip.lscce.ipsl.fr/ , focus area within 5th coupled modeling inter-comparison project (CMIP5): e.g. http://journals.ametsoc.org/page/C4MIP	Ten model comparison suggests high northern latitudes (poleward of 60° N) will be C sink to 2100, under warming and increased CO ₂	(Friedlingstein <i>et al</i> 2006, Qian <i>et al</i> 2010)

inherent model biases, or where improved SOM modeling approaches can be identified to support policy and decision making.

5. Conclusions

Our aim for this review was to connect the current state of SOM model developments to the expanding application of SOM models in policy. We see SOM modeling as entering an exciting time. New measurement methods reveal new insights for the relationship between SOM's chemical nature, spatial distribution, and dynamics in the soil environment. Advances in computational capacity and development of collaborative networks for data sharing, management, and data-model integration increasingly relieve the bottlenecks in advancing the conceptual understanding of SOM. These efforts provide better environments to apply SOM models and test hypotheses for SOM dynamics across scales. Within this context there is also room for more openly sourced involvement in model-data integration. Data management is an increasingly sophisticated branch of research. Particularly for US federally funded efforts, projects must make data management and the open provision of data a component of proposals and final products from research efforts. Libraries are developing capacity to house citable datasets, with standardized approaches to metadata and organizational structure. We believe data-model integration has only touched the surface of what is feasible, given more openly source collaborative networks of data sharing and model-data integration.

We also see the potential for SOM model applications in policy to provide an opportunity for establishing repeatable SOM modeling computational infrastructure, as well as a platform to standardize inputs, model references, and output streams. Policy applications of SOM models could support this by including sufficient metadata to repeat analyses, for example identifying the SOM model type and version, as well as the data used to drive the model and evaluate its uncertainty. Ideally SOM model applications would also be integrated within computation infrastructure with some level of open access, allowing model applications to be improved, or tested against new model versions and additional data. From the model development perspective, collaboration with model application efforts would add value by providing a standardized testbed to evaluate model improvements. This would allow SOM model developments to be more easily incorporated into model applications, better supporting policy and decision making.

Acknowledgments

Support for this work was provided by Shell Global Solutions (US), Inc, the USDA-ARS-Renewable Energy Assessment Project (REAP) (renamed USDA-ARS-Resilient Economic Agricultural Practices (REAP)), the North Central Regional Sun-Grant Center at SD State University through the US DOE—Office of Biomass Programs, award number DE-FC36-05GO85041, the USDA-National Institute of Food and Agriculture for the project 'New Tools and Incentives for Carbon, Nitrogen, and Greenhouse Gas Accounting and Management in Corn Cropping Systems' (Grant no. 2011-67003-3025), and the Colorado State University Multidisciplinary Approaches to Sustainable Bioenergy program (an Integrative Graduate Education and Research Traineeship program funded by the National Science Foundation). Dr Dimitris Stevis provided invaluable feedback during the development of section 3, examining SOM models in the context of policy applications. Many thanks to Dr Jocelyn Lavalley, Dr Jacklyn Hatala Mathes, and Sarah Fulton Smith for comments on early versions of sections 4.3, 4.5, and 4.4.

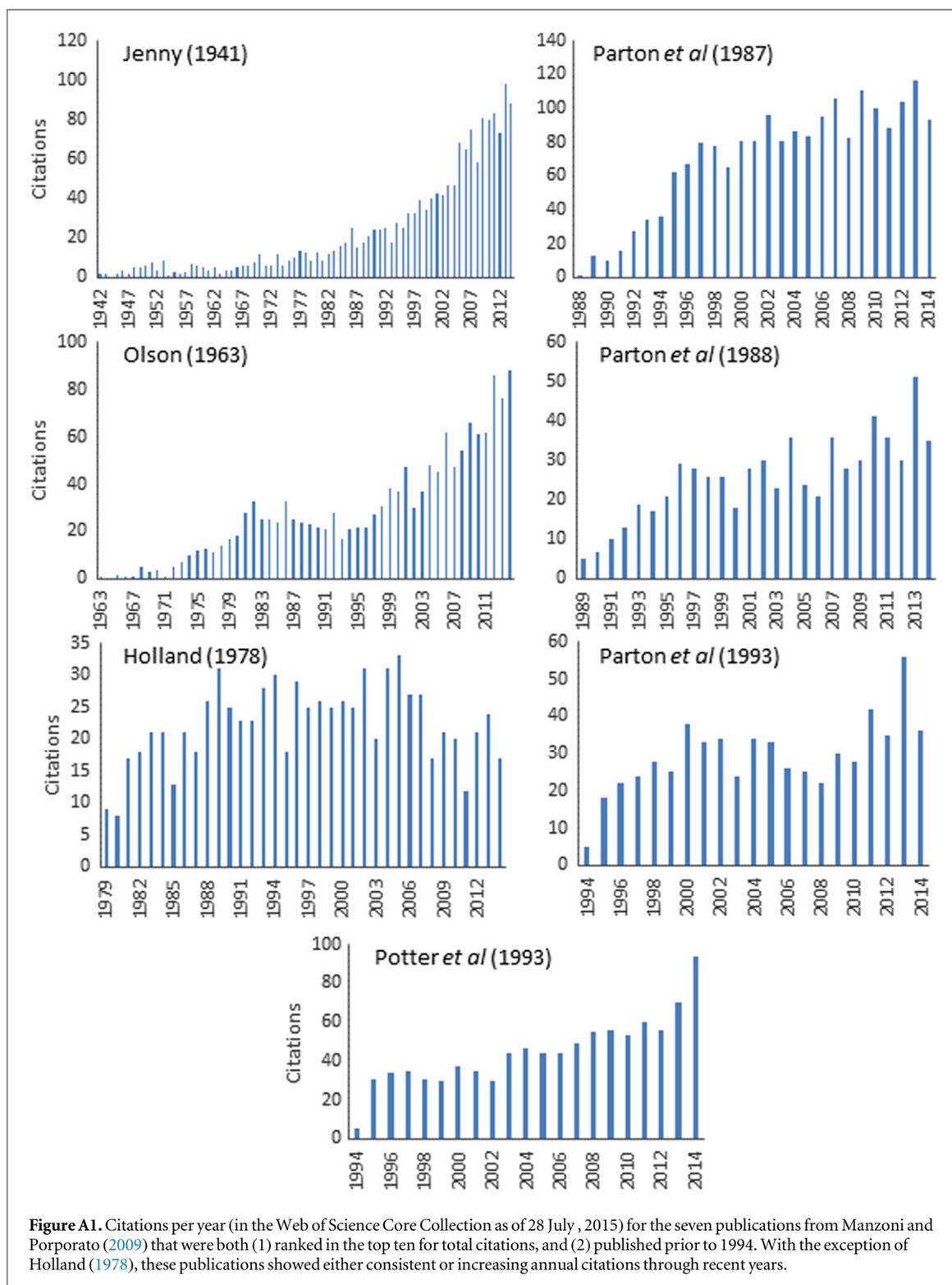
Appendix A

A1. Adjusted searches for SOM model development: models in Manzoni and Porporato (2009)

Some model publications were listed as having titles (not available) on WoS 'cited reference' of Manzoni and Porporato (2009). In those cases, titles were searched on Web of Science individually. Where they still could not be found, the citation number listed with that publication title on Google Scholar was recorded. The Google Scholar value is likely inflated relative to the WoS Core Collection value, but was used as a proxy only when no better record could be found on WoS.

A2. Adjusted searches for SOM model use: 87 named models

While the search string of <model name> AND 'soil' AND 'model' on WoS in the Core Collection worked well for unique model names, there were challenges posed by models with non-unique names. A selection of citations were evaluated in each set of search results to confirm the search yielded the specific model name of interest. When results failed to yield the model of interest, the search was either refined or manually searched to identify model publications. In some instances this yielded the targeted results. However, in



others refining was ineffective, the number of results very high (100's to 1000's), and the overall citation record for the original model publication too small to warrant manual search. For example, short model names (e.g. ELM, GEM, TCS) often were used as acronyms across many fields. If the long names of the models were similarly composed of ubiquitous terms (e.g. 'ecosystem level model', 'grassland ecosystem model', 'terrestrial carbon sequestration'), it was not

easily possible to isolate citations using the full name as a search term. Thirteen named models were excluded for this reason. Total citations yielded by these searches for the remaining 74 named models were used as a comparative measure for model uses in the scientific literature. The exclusion of models due to non-unique names suggests the potential importance of unique model names as an identifier to trace model development and uses in scientific literature.

Table A1. Complete list of all publications and named models (where model names were given) considered in the analyses for section 2.2.

Publication	Model Name	Publication	Model Name
(Aber <i>et al</i> 1978)		(Ginovart <i>et al</i> 2005)	INDISIM-S
(Aber <i>et al</i> 1991)	VEGIE	(Godwin and Jones 1991)	CERES
(Acutis <i>et al</i> 2000)	LEACHN	(Grace and Ladd 1995)	SOCRATES
(Addiscott and Whitmore 1987)		(Grant 2001)	Ecosys
(Ågren and Bosatta 1996)		(Grant <i>et al</i> 1993)	Ecosys
(Allison 2005)	EnzModel	(Griffiths and Robinson 1992)	
(Andrén and Kätterer 1997)	ICBM	(Gusman and Marino 1999)	RISK-N
(Andrén and Paustian 1987)		(Hadas <i>et al</i> 1987)	NCSOIL
(André <i>et al</i> 1994)	VOYONS	(Hadas <i>et al</i> 1998)	NCSOIL
(Baisden and Amundson 2003)		(Hansen <i>et al</i> 1991)	DAISY
(Balesdent 1987)		(Harte and Kinzig 1993)	
(Bar <i>et al</i> 2002)		(Harte and Levy 1975)	
(Beek and Frissel 1973)		(Harvey 1989)	
(Berendse <i>et al</i> 1987)		(Hassink and Whitmore 1997)	
(Birkinshaw and Ewen 2000)	NITSSHETRAN	(Hénin and Dupuis 1945)	
(Blagodatsky and Richter 1998)	NICA	(Henriksen and Breland 1999)	
(Bolin 1981)		(Holland 1978)	
(Bosatta 1981)		(Hoogenboom <i>et al</i> 1994)	DSSAT
(Bosatta and Agren 1985)	Q-model	(Hunt 1977, Reuss and Innis 1977)	ELM
(Bosatta and Ågren 1991)	Q-model	(Hunt <i>et al</i> 1983)	
(Bosatta and Agren 1994)	Q-model	(Hunt <i>et al</i> 1987)	
(Bosatta and Agren 1995)	Q-model	(Hunt <i>et al</i> 1991)	GEM
(Bosatta and Agren 1996)	Q-model	(Huwe and Totsche 1995)	WHNSIM
(Bosatta and Berendse 1984)		(Ingwersen <i>et al</i> 2008)	NICA
(Bosatta and Staaf 1982)		(Janssen 1984)	
(Botter <i>et al</i> 2006)		(Jenkinson <i>et al</i> 1990)	Rothamsted
(Botter <i>et al</i> 2008)		(Jenkinson and Coleman 2008)	Roth PC-1 (RothPC-1)
(Bradbury <i>et al</i> 1993)	SUNDIAL	(Jenkinson and Rayner 1977)	RothC
(Brenner <i>et al</i> 2001)		(Jenny 1941)	
(Bruun <i>et al</i> 2004)		(Jenny <i>et al</i> 1949)	
(Bunnell and Dowding 1973)	ABISKO	(Johnsson <i>et al</i> 1987)	
(Bunnell and Scoullar 1975)	ABISKO II	(Juma <i>et al</i> 1984)	
(Carpenter 1981)		(Kan and Kan 1991)	FERT
(Chapman and Gray 1986)		(Kätterer and Andrén 2001)	ICBM
(Cherif and Loreau 2007)		(Kersebaum and Richter 1994)	

Table A1. (Continued.)

Publication	Model Name	Publication	Model Name
(Cherif and Loreau 2009)		(Kindermann <i>et al</i> 1993)	FBM
(Chertov and Komarov 1997)	SOMM	(Kirkham and Bartholomew 1954)	
(Comins and McMurtrie 1993)	G'DAY	(Kirkham and Bartholomew 1955)	
(Craig 1957)		(Kirschbaum and Paul 2002)	CenW
(Currie 2003)	TRACE	(Knapp <i>et al</i> 1983)	
(Currie and Aber 1997)	DocMod	(Korsaeth <i>et al</i> 2001)	SOILN-NO
(Currie <i>et al</i> 1999)	TRACE	(Kravchenko <i>et al</i> 2004)	
(d'Annunzio <i>et al</i> 2008)	CEM	(Kucharik <i>et al</i> 2000)	IBIS
(Darrah 1991)		(Kuijper <i>et al</i> 2005)	
(Daufresne and Loreau 2001)		(Kuka <i>et al</i> 2007)	CIPS
(Deans <i>et al</i> 1986)		(Kumada <i>et al</i> 2008)	
(Del Grosso <i>et al</i> 2001)	DAYCENT	(Leffelaar 1988)	
(Deruiter <i>et al</i> 1993)		(Leffelaar and Wessel 1988)	
(Douglas and Rickman 1992)	D3R	(Li <i>et al</i> 1992)	DNDC
(Elzein and Balesdent 1995)		(Li <i>et al</i> 2000)	DNDC
(Emanuel <i>et al</i> 1981)		(Lin <i>et al</i> 1987)	Chenfang Lin
(Eriksson and Welander 1956)		(Liski <i>et al</i> 2005)	Yasso
(Foereid and Yearsley 2004)		(Liu <i>et al</i> 2005)	IBIS
(Foley 1995)	DEMETER	(Long and Or 2005)	
(Fontaine and Barot 2005)		(Loreau 1998)	
(Forney and Rothman 2007)		(Loreau 2001)	
(Franko <i>et al</i> 1995)	Candy	(Luo and Reynolds 1999)	TCS
(Friend <i>et al</i> 1997)	Hybrid	(Maggi and Porporato 2007)	
(Frolking <i>et al</i> 2001)	PDM	(Schwinning and Parsons 1996)	8SV
(Furniss <i>et al</i> 1982)		(Seligman and van Keulen 1981)	PAPRAN
(Garnier <i>et al</i> 2001)	CANTIS	(Shaffer <i>et al</i> 1991)	NLEAP
(Gignoux <i>et al</i> 2001)	SOMKO	(Shevstova and Mikhailov 1992)	Humus balance
(Manzoni <i>et al</i> 2008b)		(Maggi <i>et al</i> 2008)	TOUGHREACTN
Publication	Model Name	Publication	Model Name
(Manzoni <i>et al</i> 2010)		(Malamoud <i>et al</i> 2009)	Struc-C
(Mary <i>et al</i> 1998)	FLUAZ	(Manzoni and Porporato 2007)	
(Masse <i>et al</i> 2007)	MIOR	(Manzoni <i>et al</i> 2008a)	
(McCaskill and Blair 1990)	McCaskill and Blair	(Sinsabaugh and Moorhead 1994)	MEAD
(McCown <i>et al</i> 1996)	APSIM	(Sirotenko 1991)	KLIMAT-SOIL, YIELD
(McGill <i>et al</i> 1981)	PHOENIX	(Sitch <i>et al</i> 2003)	LPJ
(McMurtrie <i>et al</i> 2001)	G'DAY	(Smith 1979)	

Table A1. (Continued.)

Publication	Model Name	Publication	Model Name
(Mehran and Tanji 1974)		(Smith <i>et al</i> 1986)	
(Michalzik <i>et al</i> 2003)	DyDOC	(Stanford and Smith 1972)	
(Minderman 1968)		(Stewart <i>et al</i> 2007)	
(Molina <i>et al</i> 1983)	NCSOIL	(Svirezhev and Tarko 1981)	
(Moore <i>et al</i> 2004)		(Tateno and Chapin 1997)	
(Moore <i>et al</i> 2005)		(Thornley and Cannell 2001)	
(Moorhead and Reynolds 1991)	GENDEC	(Thornley and Verberne 1989)	Hurley
(Moorhead and Sinsabaugh 2006)	GDM	(Thornley <i>et al</i> 1995)	
(Neff and Asner 2001)	TerraFlux	(Toal <i>et al</i> 2000)	
(Neill and Gignoux 2006)		(Tonitto and Powell 2006)	
(Nicolardot <i>et al</i> 2001)		(Trumbore 1993)	
(Nikiforoff 1936)		(VanDam <i>et al</i> 1997)	NICCCE
(O'Brien 1986)	O'Brien's	(Vandclooster <i>et al</i> 1992)	Wave
(O'Brien and Stout 1978)		(van Veen and Paul 1981)	
(O'Leary 1994)	O'Leary	(van Veen <i>et al</i> 1984)	
(Olson 1963)		(Van Wensem <i>et al</i> 1997)	
(Panikov and Sizova 1996)	SCM	(Verberne <i>et al</i> 1990)	Verberne
(Pansu and Thuries 2003)	TAO	(Walter <i>et al</i> 2003)	
(Pansu <i>et al</i> 2004)	MOMOS	(Wang <i>et al</i> 2007)	
(Pansu <i>et al</i> 2007)	MOMOS-6	(Wang <i>et al</i> 2009)	
(Pansu <i>et al</i> 2009)	MOMOS-6	(Whitehead <i>et al</i> 1998)	INCA
(Parnas 1975)		(Whitmore 1995)	MOTOR
(Parnas 1976)		(Whitmore 1996b)	
(Parton <i>et al</i> 1987)	CENTURY	(Whitmore 1996a)	
(Parton <i>et al</i> 1988)	CENTURY	(Williams <i>et al</i> 1984, Jones <i>et al</i> 1984)	EPIC
(Parton <i>et al</i> 1993)	CENTURY	(Wu <i>et al</i> 2007)	SPACSYS
(Pastor and Post 1986)	JABOWA	(Zelenev <i>et al</i> 2000)	BACWAVE
(Patten 1972)	PWNEE	(Zelenev <i>et al</i> 2006)	BACWAVE-WEB
(Paustian and Schnurer 1987)		(Zhang <i>et al</i> 2007)	FLDM
(Perruchoud 1996)	ForClim-D	(Zheng <i>et al</i> 1997)	
(Petersen <i>et al</i> 2005)	CN-SIM	(Zheng <i>et al</i> 1999)	
(Porporato <i>et al</i> 2003)			
(Potter <i>et al</i> 1993)	CASA		
(Raich <i>et al</i> 1991)	TEM		
(Rastetter <i>et al</i> 1991)	MBL-GEM		
(Raynaud <i>et al</i> 2006)			

Table A1. (Continued.)

Publication	Model Name	Publication	Model Name
(Rijtema and Kroes 1991)	ANIMO		
(Robinson <i>et al</i> 1989)			
(Rosenbloom <i>et al</i> 2001)	CREEP		
(Roy <i>et al</i> 2008)			
(Running and Gower 1991)	FOREST-BGC		
(Russell 1964)			
(Russell 1975)			
(Ryzhova 1993)	NAM SOM		
(Saffih-Hdadi and Mary 2008)	AMG		
(Saggar <i>et al</i> 1996)			
(Salter and Green 1933)			
(Sanderman <i>et al</i> 2003)			
(Schimel and Weintraub 2003)			

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