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SYNTHESIS AND EMERGING IDEAS

Improving understanding of soil organic matter dynamics by triangulating theories, measurements, and models

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Abstract Soil organic matter (SOM) turnover increasingly is conceptualized as a tension between accessibility to microorganisms and protection from decomposition via physical and chemical association with minerals in emerging soil biogeochemical theory. Yet, these components are missing from the original mathematical models of belowground carbon dynamics and remain underrepresented in more recent compartmental models that separate SOM into discrete pools with differing turnover times. Thus, a gap currently exists between the emergent understanding of SOM dynamics and our ability to improve terrestrial biogeochemical projections that rely on the existing models. In this opinion paper, we portray the SOM paradigm as a triangle composed of three nodes: conceptual theory, analytical measurement, and numerical models. In successful approaches, we contend that the nodes are *connected*—models capture the essential features of dominant theories while measurement tools generate data adequate to parameterize and evaluate the models—and *balanced*—

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models can inspire new theories via emergent behaviors, pushing empiricists to devise new measurements. Many exciting advances recently pushed the boundaries on one or more nodes. However, newly integrated triangles have yet to coalesce. We conclude that our ability to incorporate mechanisms of microbial decomposition and physicochemical protection into predictions of SOM change is limited by current disconnections and imbalances among theory, measurement, and modeling. Opportunities to reintegrate the three components of the SOM paradigm exist by carefully considering their linkages and feedbacks at specific scales of observation.

Keywords Biogeochemical models · Carbon stabilization · Decomposition · Global carbon cycle · Soil organic matter

Introduction

Understanding soil organic matter (SOM) dynamics is essential to predicting the size of the soil carbon (C) reservoir and its contributions to soil function, global C fluxes, and climate change mitigation. Resolving uncertainties about the Earth system's response to environmental change requires a robust approach for evaluating SOM dynamics, an approach that integrates: (a) emerging conceptual understanding, or theory, (b) quantitative measurements, and (c) mathematical models. Accomplishing this integration essentially creates a paradigm. According to the Oxford English Dictionary, a paradigm is "a conceptual or methodological model underlying the theories and practices of a science…a generally accepted worldview." In our view, a scientific paradigm can be represented as a triangle composed of three nodes: conceptual theory, analytical measurement, and numerical models (Fig. 1a).

The first paradigm of SOM dynamics evolved early in the history of soil science and included the humic/fulvic/humin extraction approach that defined SOM in terms of solubility and chemical recalcitrance (Waksman 1927) and a simple one-pool model was developed to describe and predict SOM changes (Salter and Green 1933). By the 1980s, other ideas emerged to explain the stability and turnover of SOM. Researchers integrated incubation studies, radiocarbon dating, aggregate separation, and other methods to develop the idea of compartmentalizing soil carbon into pools with different turnover times (Paul 1984). Even with 1980s computing power, scientists were able to incorporate these conceptual pools into simulation models that were able to effectively describe observed large-scale patterns of SOM dynamics (van Veen and Paul 1981; Parton et al. 1987) and an early SOM paradigm formed.

The current dominant paradigm continues to conceptualize soil as discrete C pools with differing turnover times (theory). Carbon pools and turnover can be parameterized from experiments or measurements that include: respiration time courses during laboratory incubations, isolation of SOM pools by physical properties (such as size or density), and radiocarbon analyses (measurement). Flow between pools is governed by first-order kinetics driven by pool size and modified by environmental conditions (model). This assumption provides the basis for soil profile-scale models such as CENTURY (Parton et al. 1987) and RothC (Jenkinson and Rayner 1977), which have been used widely to explore SOM dynamics and form the core soil biogeochemical component of Earth system models (Todd-Brown et al. 2013).

This approach is robust and has stood the test of time because all three elements (theory, measurement,

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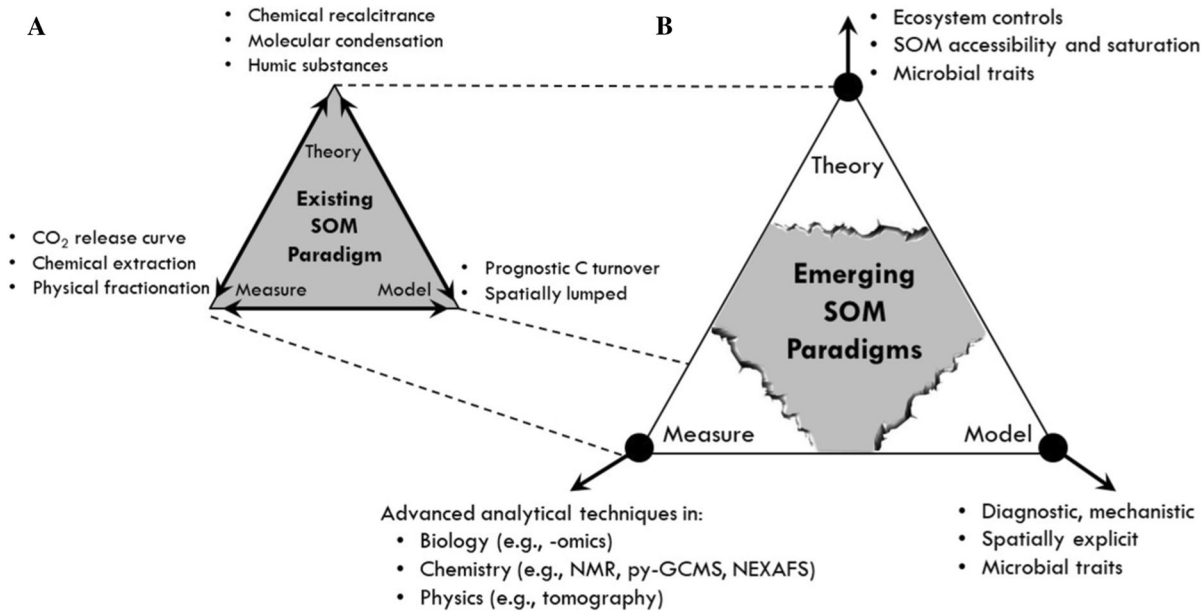

Fig. 1 A representation of existing and emerging approaches to evaluating soil organic matter (SOM) dynamics. The existing approach is robust because all three nodes—theory, measurement, and modeling—form strong bidirectional linkages and are well balanced (**a**). Recent and ongoing innovation at each node expands the SOM paradigm triangle as understanding of the controls on SOM dynamics grows. However, if expansion at a node outpaces integration of linkages within the triangle, then cracks form causing a lack of applicability and adaptability to changing environmental conditions (**b**)

and model) are adaptable, linked and, simply, it worked. This paradigm persists because it captures a general principle of SOM dynamics, that SOM is heterogenous and comprises carbon pools that decompose at different rates. With multiple pools and turnover times, most observed changes in carbon mass over time can be simulated, but often by calibrating the model with different pool sizes and decay constants unvalidated by measurement. The empirical models are simple enough to be adapted to different theories about SOM stability, distribution among pools, and factors influencing destabilization. Yet, this paradigm also has been criticized for its simplicity, i.e., it is oversimplified and excludes many systems that are not "typical." Finally, the existing paradigm is not well suited for dealing with rapidly changing environmental conditions such as those developing with climate change. To address the limitations inherent to first-order models, many exciting new theories, measurements, and models emerged during the early 2000s (Fig. 1b). But, the paradigm was left unbalanced.

New work has advanced individual, or pairs of, nodes of the SOM triangle. But, there has been little focus on evaluating how these developments can be integrated to form a new, cohesive, stable paradigm (Don et al. 2013). In agreement, Bradford et al. (2016) concluded that, "the major modeling uncertainty is associated with representing common and outdated ideas about soil C turnover," and suggested that confidence in model predictions of SOM is diminished because assumptions underlying SOM formation and stabilization in climate models often conflict with our emerging understanding. The existing paradigm worked well because concept, measurement, and model formed strong connections that reinforced each other. It is difficult, however, to evolve to new theories, measurement approaches, and numerical models within an existing paradigm—the whole triangle must be evaluated as a unit. *We argue that recent discoveries pulled on the nodes of the existing SOM paradigm triangle causing discontinuities, or "cracks."*

Developments causing disconnections in our understanding of soil organic matter dynamics

Developments in theory

Theoretical and conceptual understanding drives how we design experiments, collect measurements, and frame the construction of numerical models. Recent advances in conceptual theory refined our view of SOM persistence as an ecosystem property (Schmidt et al. 2011) and provided nuance to our understanding of how soil properties and organisms interact to determine the balance of C in a given system, for example, (1) the "onion layer" concept of organo–mineral interaction, (2) C saturation, (3) microbial accessibility, and (4) metabolic/functional traits of the microbial assemblage. Some of these advances are purely theoretical, while others are measurable or model-able, however none have yet to fully develop in all three nodes across scales.

In 2007, Kleber et al. advanced the conceptualization of SOM–mineral interactions by proposing that layers of different types of organic molecules self-assemble on mineral surfaces; e.g., amino acids have strong affinity for mineral surfaces, while more aliphatic molecules interact more readily with the organic "tails" of those amino acids. This "onion-layer" theory of SOM–mineral interaction provided a compelling insight into organic matter stabilization and supported another emergent concept of soil C saturation (Six et al. 2002; West and Six 2007). Contrary to the prior assumption of a linear increase in soil organic C stocks with increasing inputs, C saturation theorized that soil C storage efficiency decreases as a soil approaches an asymptote, or saturation (Stewart et al. 2007, 2008). Mineral-bound C saturation may be attributable to the finite amount of mineral surface area onto which organic matter sorbs (Hassink 1996). Because they are less protected from decomposition by mineral association, particulate organic matter fractions are less likely to saturate.

These theoretical developments are difficult to verify experimentally because the critical measurements are challenging to make. A mono-layer equivalent level of C loading ($\sim$ 1 mg C m^{-2} mineral surface) was used to describe stabilized soil C from both theoretical and empirical perspectives (Mayer 1994), and the nanometer-scale layering of molecules on soil particle surfaces is gaining evidence (Petridis et al. 2013; Mitchell et al. 2018). Yet, the specific surface area of soil minerals and their coverage or saturation with organic matter are difficult to quantify (Kaiser and Guggenberger 2003; Wagai et al. 2009). These theoretical developments are appealing, extensively cited, provide new perspectives on soil C stabilization and destabilization, and are beginning to be implemented in numerical models (e.g., Wang et al. 2013; Ahrens et al. 2015). But, their long-term adoption will depend on identifying measurements that are suitable proxies of the phenomena that reflect differentially stable soil C pools; yet, consensus on how to determine soil C saturation capacity from measurements of reactive surface area, or other inherent soil properties, is lacking.

Recent theoretical advances (e.g. Schmidt et al. 2011; Schimel and Schaeffer 2012) argue that the primary factor regulating the rate of microbial use of organic compounds is physical access to those molecules, rather than metabolic capacity to break them down. In soil's complex three-dimensional mineral matrix, microbes gain access to otherwise protected organic compounds through aggregate disruption, desorption, and diffusion. Once accessible, the fate of C depends on how microbes allocate it within their metabolic processes. For example, do they respire it or convert it to cell constituents, exoenzymes, and extracellular polymeric substances? Or, is it deposited into the soil environment as microbial detritus to be stabilized by aggregation or mineral interactions (Kallenbach et al. 2016)? While the role of microbial accessibility and allocation in SOM stabilization gained recognition, the role of chemical recalcitrance concurrently declined (Dungait et al. 2012; Schimel and Schaeffer 2012). Unfortunately, the spatial scale at which these soil processes operate makes it challenging to incorporate these emerging theories about microbial access and allocation into simulation models or even experimentally test them through direct measurement.

In summary, recent theories treat SOM persistence as an ecosystem property resulting from the balance between decomposition by microorganisms and protection by physical and chemical processes (e.g., aggregation and mineral association; Schmidt et al. 2011; Lehmann and Kleber 2015). As such, climate and soil mineral composition can be dominant controls on SOM stabilization (e.g., Marín-Spiotta et al. 2014; Doetterl et al. 2015; Lawrence et al. 2015; Khomo

et al. 2017). Limited physical accessibility of SOM to microbes (Dungait et al. 2012; Schimel and Schaeffer 2012), saturation dynamics (Six et al. 2002; Stewart et al. 2008; Castellano et al. 2015), and microbial community metabolic/functional traits (Averill et al. 2014; Bier et al. 2015; Hawkes and Keitt 2015; Leff et al. 2015; Averill and Hawkes 2016) also are recognized as important processes in SOM stabilization. These new theories changed our conceptual understanding of the nature and dynamics of SOM, but remain largely disconnected from measurements and models.

Developments in measurements

Measurements and observations are necessary to inform and test theories, and to parameterize and validate models. Recent advances in analytical techniques immensely expanded our ability to characterize SOM and the factors regulating its fate, including: (1) SOM chemical composition, (2) the molecular biology and community composition of the microbial agents acting on it, and (3) the physical structure of the soil matrix. In some cases, this new wealth of analytical power has exceeded both our ability to interpret these data and to incorporate them into numerical models.

To characterize the chemistry of extractable SOM, a number of spectroscopic methods are available, ranging from relatively simple ultraviolet/visible spectroscopy (Weishaar et al. 2003) to ultra-high-resolution electrospray ionization Fourier-transform ion cyclotron resonance mass spectrometry (ESI-FT-ICR-MS) (Sleighter and Hatcher 2007). While these methods are capable of generating thousands of data points per sample, they rely on mobilizing SOM from the mineral matrix using different extractants that often compromise the very compounds we want to characterize (Tfaily et al. 2017).

Unextracted SOM can be assessed using solid-state methods such as: ^{1}H NMR spectroscopy for mineral-free organic particles or ^{13}C for bulk SOM (Wilson 1987; Simpson and Simpson 2014), Fourier Transform Infrared Spectroscopy (FTIR; Ellerbrock and Gerke 2013) in the mid- and near-infrared regions, analytical pyrolysis (such as pyrolysis gas chromatography-mass spectrometry; GC–MS; Saiz-Jimenez 1994), and near-edge X-ray adsorption fine structure (NEXAFS) spectroscopy (Gillespie et al. 2015). These modern analytical methods allow us to characterize the chemical composition of SOM more-or-less in situ, and offer an unprecedented level of chemical detail on the nature of SOM at the molecular and functional group scales. Yet, these measurements do not necessarily connect well with mechanistic theory or numerical modeling.

Microbial communities characterized with DNA- and RNA-based methods provide thousands to millions of sequences from gram-quantities of soil, each sequence representing a different taxon (and some DNA may come from dead cells; Carini et al. 2016). This volume of data makes using "-omics"-based approaches in biogeochemical models a surpassing challenge (Schimel 2016), despite there being great interest in tying the composition of the microbial community to its functioning (e.g., Torsvik and Øvreås 2004; Allison and Martiny 2008; Evans and Wallenstein 2014; Harter et al. 2014). To identify microbial functioning more specifically, researchers have targeted functional genes, yet the presence of a gene for a protein does not indicate that the gene is actually being transcribed or the enzyme synthesized, and also does not predict the functional characteristics of the enzyme once it is synthesized (Prosser 2015). Thus, -omics approaches to study microbial communities are powerful for evaluating the composition and potential activities of the microbial community—they have revolutionized microbial ecology—but their ability to offer useful information on SOM dynamics remains questionable.

A potential approach to integrating microbial community data with concepts and models is focusing on "microbial traits." Different from prior work on microbial traits such as growth rate, yields, maintenance versus growth respiration determined in laboratory conditions, recent advances seek similar metrics for much more dynamic populations in situ. Individuals with different distributions of functional traits may correspond to different taxa of organisms, and different suites of traits (e.g., life history strategies) may be selected for by environmental conditions that in turn drive biogeochemical processes. Such trait-based modeling has proven successful in both plant ecology and marine microbiology (Barton et al. 2013; Dutkiewicz et al. 2013; Reich 2014). For example, in the marine environment the distribution of distinct groups of phytoplankton correspond to traits such as photosynthetic activity. Trait approaches can collapse substantial phylogenetic variation into a manageable

number of functional "types" based on life history strategies. Models that select from trait distributions do not require a priori definition of those life history strategies and offer potential for SOM studies (e.g., Allison 2012; Kaiser et al. 2014; Manzoni et al. 2014).

One of the most important advances in characterizing the physical soil matrix has been the development of non-destructive visualization methods such as X-ray tomography, which provides a three-dimensional representation of a soil's architecture based on the contrasting density (or absorbance) of its constituents (Cnudde and Boone 2013). As technological advances have improved the spatial resolution and chemical sensitivity, micro X-ray tomography now allows resolving the arrangements of water films, roots, soil minerals, and microbes. These analyses enable the localization of SOM within the three-dimensional soil pore structure (Peth et al. 2014). Such micro-scale soil "maps" can help inform future measurements by indicating potential microsites for SOM stabilization through co-location among minerals, aggregates, roots, and microbes (Kinyangi et al. 2006; Vidal et al. 2018). However, linkages with theories and models need to be strengthened: can SOM accessibility be quantified using micro-tomography? Could tomographic measurements be better aligned with emerging pore-scale models (Ebrahimi and Or 2016; Manzoni et al. 2016; Segoli et al. 2013; Vogel et al. 2015;) to identify which microsites are likely to protect organic matter for centuries? How might we distill such insights to a scale where we could improve whole-soil or larger-scale models?

In summary, innovative measurement techniques have caused further discontinuities within the existing SOM paradigm. In part, new measurement approaches have emphasized high-resolution data: X-ray tomography can map the three-dimensional pore structure of a soil core; mass spectrometry techniques can identify thousands of individual molecules; and genomic tools can identify tens of thousands of microbial taxa. But, integrating these high-resolution data into emerging concepts and theories is challenging because of the sheer volume of data and potential mismatches in scale. Even greater challenges are encountered if these data are used to calibrate numerical models, whose tens of state variables are being mapped against thousands of driving variables (Schimel 2016).

Developments in simulation models

Numerical models provide tools that approximate theoretical understanding while integrating measurements to test assumptions and make predictions about potential responses to perturbations. Recent advances include: (1) process modifiers to encompass greater complexity, (2) microbial-explicit models, and (3) reactive transport models. With some models reaching up to 180 variables describing decomposer dynamics, including different element pools and different decomposer groups (Grant 2001), and still others based entirely in theory, problems with data limitations such as poor coverage or inconsistent methods keep the triangle unbalanced.

Litter decomposition and SOM models have expanded from their origins as simple one-pool models (Salter and Green 1933) to include greater structural complexity that allows them to cover broader geographic ranges, a wider array of environmental conditions, and longer temporal scales (Jenny et al. 1949; Olson 1963; Manzoni and Porporato 2009; Sierra and Müller 2015). Facilitated by advances in computing power, this expanded capacity allows extrapolating model projections beyond the data and theoretical domains over which they were conceived (Bradford and Fierer 2012). For example, although the CENTURY model was conceptualized at the monthly time scale and parameterized for grassland systems in the central United States (Parton et al. 1987; Schimel et al. 1994), CENTURY-like implementations at daily and even hourly time scales are now common in the terrestrial components of nearly every Earth system model used to project global C cycle-climate feedbacks (Todd-Brown et al. 2013). Modifications to global-scale models change the magnitude of soil C feedbacks to the climate system (Jones et al. 2005; Koven et al. 2015), highlighting the importance of resolving structural uncertainties in these models. The sensitivity of these models also highlights potential limitations in both their theoretical underpinnings and of the data available to evaluate model predictions under novel conditions (Luo et al. 2015). For example, generally soil C flux models based on theories of chemical recalcitrance are relatively insensitive to soil moisture—less sensitive than experimental data indicate (Lawrence et al. 2009; Carvalhais et al. 2014). This suggests that the theories and mechanisms describing how soil moisture influences

biogeochemical fluxes are poorly represented in "standard" models (Moyano et al. 2013; Sierra et al. 2015). Globally gridded estimates of soil C concentrations can be used to evaluate the belowground stocks simulated by biogeochemical models (Hararuk et al. 2014; Wieder et al. 2014). Fewer data, however, are available to parameterize or evaluate how plant residues are transformed into stable organic matter, or to quantify long-term SOM persistence in soils.

Most simulation models focus on SOM dynamics without explicitly representing SOM as microbial substrate; therefore, considering microbial agents in biogeochemical models represents a relatively recent evolution (Schimel and Weintraub 2003; Allison et al. 2010). Ideas about microbial roles in SOM dynamics are not new (Tenney and Waksman 1929; Monod 1949; Parnas 1975). Several nonlinear models in which microbes were explicitly described and interact with decomposition emerged in the late 1970s and early 1980s (Harte and Levy 1975; Parnas 1975; Smith 1979; McGill et al. 1981). The new generation of so-called "microbial models" explicitly considers microbial agents through theoretical investigations of microbial community composition (Allison 2012; Waring et al. 2013; Kaiser et al. 2014), trying to predict microbial activity as measured by laboratory incubations (Wang et al. 2015), ecosystem-scale representation of biogeochemical dynamics (Sistla et al. 2014; He et al. 2014), and even global-scale projections that incorporate simple representations of microbes (Sulman et al. 2014; Wieder et al. 2015). These modeling expansions apply structures that fundamentally change the theoretical assumptions and numerical representations of soil biogeochemical dynamics; thus, they alter model responses to environmental perturbations (Wieder et al. 2013; Hararuk et al. 2015; Tang and Riley 2015). In doing so, microbial-explicit models present opportunities to explore effects of emerging theories about the influence of microbial physiology and functional community composition on SOM formation and responses to environmental changes (Grandy et al. 2009; Cotrufo et al. 2013; Bradford et al. 2016; Buchkowski et al. 2017). Peering into microbial physiology and functioning in soil biogeochemical models is appealing, but doing so generates enormous challenges in translating available data and theory into models that accurately represent microbial agency at appropriate scales.

Reactive transport models have been used in a wide variety of applications, including contaminant transport and transformation, biogeochemical redox cycling, chemical weathering, and geologic C sequestration (Steefel and Maher 2009). The capacity of these models to capture processes influencing soil C cycling and stability is, however, increasing (Lawrence et al. 2014; Riley et al. 2014; Li et al. 2017). In exploring their application to SOM dynamics, we push the limits of data currently available to constrain the heterogeneous reactions that define organic matter behavior in soils. The measurements necessary to constrain these models are well prescribed: they include the stoichiometry of the relevant reactions, associated mineral volume fractions, surface areas, temperature-dependent equilibrium or partition coefficients, and kinetic rate constants. However, these data are not easily derived from common and widespread measurements. Current models target multiphase aqueous and gas transport, heterogeneous transport pathways, the interactions of microbial populations, redox cycling and the associated relationships between metals and organic matter, and the complexity of multi-site competitive surface complexation and ion exchange (Lawrence et al. 2014; Riley et al. 2014; Li et al. 2017). But, the most difficult challenge lies in quantifying the rate constants and equilibrium partitioning coefficients for multiple compound classes or SOM components. With thousands of distinct molecules in soil that can react in a diversity of ways, reactive transport modeling approaches thus present computational and analytical obstacles. However, they also potentially serve as both a diagnostic and predictive tool for SOM dynamics and offer an opportunity for addressing novel hypotheses.

As we further develop models that can incorporate the complexity of microbial communities, organic matter, and physical structure, it is worth noting that many of the most sophisticated microbial models still contain only three functional groups of microorganisms (Manzoni and Porporato 2009). For example, one such model (Kaiser et al. 2014) contains plant degraders, microbial necromass degraders, and opportunists. Yet another model—the guild decomposition model (Moorhead and Sinsabaugh 2006)—contains three groups of microbes: opportunists, decomposers, and miners (lignin-degraders). Another model contains one microbial biomass pool (Sistla et al. 2014),

but three classes of enzymes. Further, the biomass pool is stoichiometrically flexible and can change the C/N ratio to reflect shifts among bacteria and fungi.

Finally, emerging numerical models are stretching the existing SOM paradigm. Recent work such as the Millennial model (Abramoff et al. 2018) aim to be diagnostic and mechanistic, where the turnover time of SOM is more directly linked to the timescales of physical protection and isolation. Thus, there is a shift from an *implicit* incorporation of spatial heterogeneity and biological activity to an *explicit* incorporation of physical soil structure (e.g., Monga et al. 2014), SOM chemistry (e.g., Riley et al. 2014), and microbial traits (e.g., Manzoni et al. 2016). However, the physical, chemical, and biological parameters, as represented in models, are not always tightly linked with theory or measurements. For example, models that drive decomposition through the activity of specific microorganisms necessarily collapse decomposers into a small number of conceptual groups.

Summary of recent developments

Our perception of SOM dynamics is changing, shifting to finer-scale, mechanistic perspectives. Simultaneously, there is increasing demand for data about SOM dynamics at landscape to global scales. In other words, our capacity to observe and understand small-scale processes has increased, while the spatial and temporal scope of the questions we are asking has increased to the globe and over centuries. Therefore, as our perceptions change, we need new triangles that can help address pressing questions related to SOM research: How can we incorporate new theories about physical protection and microbial residues in a framework that can help us address global-scale phenomena? How do we incorporate the wealth of data being generated into new mathematical theories and simulation models that spans across scales? How can we determine particular mechanisms at the interface of microbes, mineral surfaces, and physicochemical interactions that are relevant for the global carbon cycle and changes of Earth's climate?

Rapid innovation in theoretical developments, analytical measurement capabilities, and numerical model constructs of SOM dynamics are critical for filling in basic knowledge gaps. In isolation, however, such advances do not necessarily improve our holistic understanding of SOM dynamics, its vulnerability to environmental change, or opportunities to increase C sequestration. Emphasis on theory, measurement, or modeling within a study tends to result in disciplinary insights, but the integrated perspective needed to transform our thinking about how soils function must happen collectively over time. We are in a transition; the next phase of advances in our understanding will require the search for re-connectivity within new SOM paradigms.

Developing newly connected and balanced soil organic matter paradigms

The 1980s concepts and generation of SOM models based on turnover-time-defined C pools are now failing to meet developing needs to characterize fine-scale mechanisms of SOM turnover and large-scale patterns of SOM dynamics in a rapidly changing environment. Decades of research and seminal papers (e.g., Schmidt et al. 2011; Lehmann and Kleber 2015) have cracked the SOM paradigm, but we haven't replaced it with a new one. What do we *do* with our new theories, measurements, and models? We don't just need a new model, we need a new framework to tie together theories, measurements, and models.

Thus, we argue that the SOM paradigm is broken and needs reintegration. Chemists, microbiologists, and large-scale modelers have been pushing forward separately. Each of these research threads is offering deep and fundamental contributions to our understanding of the processes that drive SOM dynamics; however, they remain largely disconnected from each other and are only beginning to gel to create a new dominant paradigm that would reintegrate the nodes of the triangle. For example, advances in analytical techniques for characterizing SOM composition could be better aligned with representation of the organic constituents in reactive transport models, such that measurable classes of compounds correspond directly with those in the models.

As concepts evolve, and as tools develop, measurements and models based on outdated theory may need to be abandoned rather than "repaired" by patching up the cracks. The dominant current triangle based on pools of soil C with different turnover times, which led to the phenomenally successful CENTURY and RothC models, has reached its limits. To move past, to be able to predict how SOM will respond to

rapid changes in climate and land management, and to do so robustly enough to support high-level policy development, we need to either develop a new paradigm structure based on current theories, or look back at previous theories that have lacked popularity, but contain innovative ideas. Developing this new framework will remain an iterative process of trial, error, and exploration. One recent step along this road was the Millennial model which relies on measurable soil C pools and key physical and microbial processes (e.g. sorption/desorption and depolymerization; Abramoff et al. 2018). Reactive transport models have also been used previously with some success (Elzein and Balesdent 1995; Braakhekke et al. 2013, 2014), and may be best used in the future at an intermediate level of complexity as a blended pool-transport model, adding more processes than a traditional model, but not requiring a full-blown transport model with detailed chemistry. Our first recommendation, therefore, to help reintegrate the SOM paradigm triangle is for researchers to continue in this line by more explicitly considering how their work connects to other perspectives (i.e., other nodes in the triangle). Soil microbiologists, chemists, and physicists need to interact more effectively—i.e. a regrowth of *soil science*.

To imagine that a single triangle will emerge that applies at all scales and soil processes is, however, almost certainly a false expectation—a paradigm triangle that is well-integrated at the scale of mineral surfaces, organic matter sorption, exoenzyme activity, and microbial sequencing would not also describe global-scale C dynamics. The paradigm structure we are migrating to, thus, instead of being a single new triangle, may more likely be a "stack" of triangles, each focusing on a different scale, at which different processes dominate biogeochemical dynamics. A key challenge will therefore be to ensure that larger-scale models engage the new paradigms that develop from finer scales—large-scale analysis must remain grounded in solid mechanistic understanding of the underlying processes.

For example, high-resolution micro-scale models can generate dynamics that may be fundamental to explaining how C is decomposed and recycled, but at longer time-scales, those dynamics can become effectively a blur of activity—"*sound and fury, signifying nothing.*" In contrast, big-but-slow processes, such as soil mixing or weathering, that have little influence on seasonal to annual timescales might emerge as critical at the decadal to centennial scales. Tools exist for identifying which processes operate at timescales relevant for specific questions and which can be collapsed by assuming effective steady-state (e.g., Manzoni et al. 2016). Such approaches can allow climate to set the stage for local-scale microbial communities, as well as soil conditions (e.g., parent material mineral assemblage) that control how microbial products are stabilized (e.g., Rasmussen et al. 2018; Rowley et al. 2018).

Developing landscape- and soil profile-scale triangles must capture the essential behaviors that dominate at the mineral particle-scale (e.g., protection/sorption vs. microbial metabolism), yet must still capture the phenomena that dominate at larger scales (e.g., topography and vegetation type). Thus, one might not need to explicitly capture the complex dynamics of microbial communities within a large-scale model—if you understand the drivers of the functional responses, you can "model past the microbes" (Schimel 2001), and so capture the essence of microbial dynamics in a mathematically tractable way. Such approaches allow us to capture high-resolution information to inform models that operate at larger scales, yet scales appropriate for linking with global climate models.

Part of the challenge moving forward, therefore, will be to extract the essential fine-scale behaviors that larger-scale models should capture. Scaling these insights into societally relevant theories and models is critical to advancing biogeochemical understanding in the twenty-first century and to supporting policy and land management. Reaching this level requires that we acknowledge that the paradigm triangle that has served us well for 30 years has reached its limits; to meet the new demands being placed upon soil scientists, the existing triangle should be modernized, if not completely replaced. The replacement will likely be an integrated bundle of triangles, each with a coherent internal intellectual structure that functions at one of the critical scales of space and time. In many ways, the theory, measurements, and models that will form these new paradigms already exist. The first challenge is to assemble these parts to achieve balance and parsimony. The next challenge is to link these sub-paradigms across spatial and temporal scales such that the essential mechanistic richness of the small scale is honored appropriately at the large scale.

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