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Key Poin ts:
- Environmental =ch networks can make important contributions to advance our understanding of soil organic matter(SOM) dynamics
- These networks generate unique, complementary, long-term SOM data setscovering multiple scales, gradients, and responses to change
- For maximum impact, nernorlc data must be discoverable, comparable , and betterintegrated with numerical modelingefforts

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Leveraging Environmental Research and Observation Networks to Advance Soil Carbon Science

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Abstract Soil organic matter (SOM) is a critical ecosystem variable regulated by interacting physical, chemical, and biological processes. Collaborative efforts to integrate perspectives, data, and models from interdisciplinary research and observation networks can significantly advance predictive understanding of SOM. We outline how integrating three networks- the Long-Term &:ological Research with a focus on ecological dynamics, the Critical Zone Observatories with strengths in landscape/geologic context, and the Nationa l Ecological Observatory Network with standard ized multiscale measurements- can advance SOM knowledge. This integration requires improveddata dissemination and sharing, coordinated data collection activities, and enhanced collaboration between empiricists and modelers within and across networks.

1. Introduction

Understanding and predictingsoil organic matter (SOM)dynamicsis an inherently complex, interdisciplinary challenge with broad societal relevance (Campbell &Paustian, 2015; Davidson&Janssens, 2006; Harden et al., 2018; Jac kson et al., 2017). SOM contains the largest actively cycling terrestrial carbon (C) pool and plays a key role in global-to-local biogeochemical and water cycling by influencing soil fertility, nutrient availability, water holding capacity, and infiltration rates (Lal, 2016). These ecosystem services are essential in managed systems, for the production of food, fiber, and fuel and in natural systems for providing habitat and mediating ecosystem productivity and resiliency (Adhikari & Hartemink, 2016). The formation and decomposition of SOM are driven bya number of interacting physical, chemical, and biological mechanisms occurring across a range of spatiotemporal scales (Lehmann & Kleber, 2015; O'Rourke et al., 2015; Schmidt et al., 2011). Despite recent conceptual advances, significant uncertainties remain regarding the magnitude and spatial distribution of SOM s tocks, their inherent stability, and the cascading effects on ecosystem and critical zone processes. Th us, our fun damenta l understanding of the ecological and physicochemical controls on the capacity of Earth's soils to store organic C, now and in the future, remains incomplete.

An improvedgrasp on SOM dynam ics and their response to natural and anthropogenicperturbations inherently depends on synthesis of perspectives and models from distinct yet overlapping research communities and disciplines. Recently, Harden et al. (2018) articulated a vision to advance SOMscience by identifying key data sets needed to advance understand ing of soil C (de)stabilization mechanisms, disseminating and sharing those datasets across disciplines and communities, and developing modeling platforms to link data and models acrossscales. Furthe r, Hinckley et al. (2016)and Baatz et al. (2018)argued that synthesis of data and models from complimentary, long-term environmental research and observation networks (hereafter, " networks") can greatly enhance conceptual and numerical modeling of Earth system dynamics. Building on

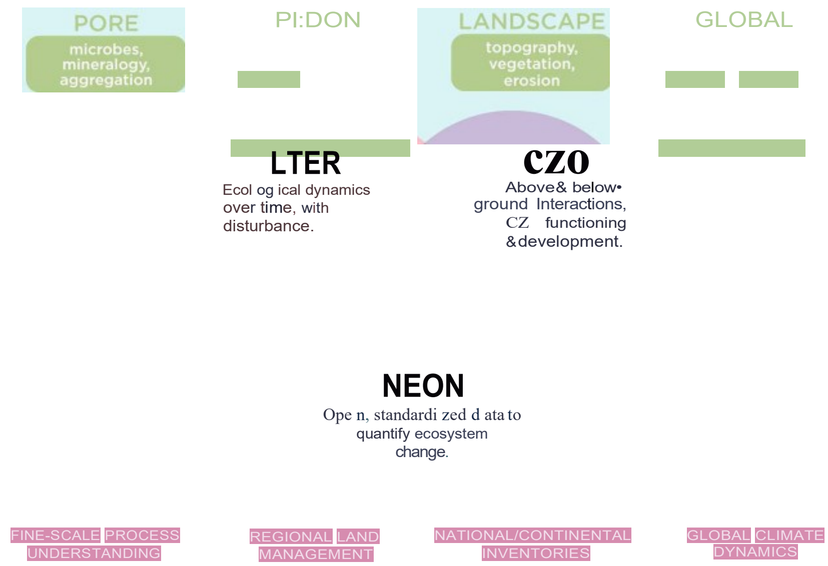

Figure L Conceptual model of network foci and their overlapping interests in soil organicmatter (SOM),with multiscale controls on SOM dynamics on top and cross-scale impacts of advances in SOM understanding and prediction beneath. LTER is th e Long-Term Ecological Research networ k, CZO is the Critical Zone Oooervatory network (CZ is the critical zone), and NEON is the National Ecological Oooervatory Network.

these efforts, we assert that networks can play a unique and important role in catalyzing breakthroughs in understanding and predicting SOM and its response to environmental change. No single network can provide the diversity of disciplinary perspectives and gradients, nor the necessary data in adequate spatiotemporal detail, required to calibrate mechanistically accurate soil biogeochemical models, assess their output, and develop improved process representations. However, when viewed as a consortium of complemen tary networks, the U.S.-based Long-Term Ecological Research (LTER) network, the Critical Zone Observatory (CZO) network, and the National Ecological Observatory Network (NEON) provide a su ite of powerful and synergistic observational platforms that can contribute substantially to SOM science.

A compelling aspect of these networks that underscores their collective potential is that each emerged in response to community needsin a set of complementary intellectual heritages. LTERgrew out of the ecosystem ecologytradition and the need for long-termstudies across a diverse range of Earth's biomes.The CZO netwo rk arose from a community of geologists, geomorphologists, soil scientists, and hydrologists who sought to advance mechanistic understanding of how the Critical Zone evolves and functions in response to forcings from above (e.g., vegetation and climate) and below (e.g., tectonics). Meanwhile, NEON grew out of the desire for a standardized suite of ecological observations that could support continental-scaleecological forecasting. From these vantage points, SOM represents an emergent Earth system property that links these networks together, intersecting core cross-network interests, data, and activities (Figure 1). As soils sit at the interface of the biosphere and lithosphere, reciprocal network strengths in biological and geoscience disciplines(Rich ter et al., 2018), combined with data collection across scales and wide gradients in controlling factors, can produce transformative insights into SOM dynamics- if network data are shared, synthesized, and integrated. Here we seek to (1) highlight network strengths that provide complement ary, novel insights into SOM dynamics and (2) articulate opportunities to maximize network contributions to advance unders tanding and prediction of SOM stocks and fluxes.

2. SOM Insights From Research and Observation Networks

Coordinated data collection and modeling are needed to accurately understand and project SOM trajectories in response to environmen tal change(Knapp et al., 2012; Y. Luo et al., 2016;Vereecken et al., 2016). Despite the outsized significance of SOM in understand ing global carbon budgets, this coordination is often lacking.

The problem is exacerbated by the heterogeneity of different mechanisms responsible for SOM persistence at different scales (Figure1; Hinckley et al., 2014; O'Rourke et al., 2015). For example, at the pore scale, SOM dynamics are controlled byphysicochemical processes suchas mineral sorption, aggregation, and redox conditions(Chen et al., 2014; Keiluweit et al., 2017; Six et al., 2002; Von Ltitzow et al., 2008; Yan et al., 2016), as well as biotic processes such as microbial substrate use efficiency (Manzoni et al., 2012) and root activity (Keiluweit et al., 2015). At broader scales, other factors regulate SOM, including parent material and land use at pedon scales (Catoni et al., 2016; Guo& Gifford, 2002; Post & Kwon, 2000; Wagai et al., 2008), vegetation, topography and erosion at landscapescales (Ritchie et al., 2007; X Wang et al., 2014), and primary production and climate at continental to global scales (Koven et al., 2017; Figure 1). SOM conceptual and numerical frameworks thus require expert knowledge and data from across the biogeosciences, as well as synthesis of observations and insights from particles to biomes. Numerical models are beginning to include more realistic representations of physical, chemical, and biotic processes across scales(e.g., soil physical protection and microbe-SOM interactions ; sensu Abramoff et al., 2018; Sulman et al., 2014;Tang & Riley, 2015; G. Wang et al., 2015; Wieder, Grandy, et al., 2015), yet challenges remain. Diverse multicompartment data sets spanning spatiotemporal scales are thus needed to help develop, calibrate, and validate mechanistically accurate, cross-scale models (Y. Luo et al., 2016; Sulman et al., 2018; Wieder, Allison, et al., 2015). Here the networks can make a substantial contribution.

A key role of the LTER network is to provide an ecological context forSOM dynamics. Results from this network demonstrate how biotic properties (biodiversity, productivity, and succession) interact with physical conditions and disturbances to influence soil C and nutrient cycling over time (Hinckley et al., 2016; Richter et al., 2018). For instance, research at LTER sites has demonstrated the importance of forest age (Fahey et al., 2005), forest type (Crow et al., 2009), and biotic interactions (Crowther et al., 2015) in driving storage capacity and forms of SOM. While they excel in providing long-term observations in a diversity of ecosystems (28 locations covering most major biomes), many LTER sites concurrently maintain long-running manipulative experiments. These provide critical insights into how changes in biodiversity (Fornara & Tilman , 2008), nutrient enrichment (Frey et al., 2014; Riggs et al., 2015), agricultural management (Grandy & Robertson, 2007), and climate change (Melillo et al., 2017) alter SOM pools and fluxes. Such experiments provide much-needed opportunity to investigate possible unexpected, dramatic SOM responses in particular ecosystems and improve our ability to model them, given that, even when soil models match observations at steady-state or in the past, they often diverge under future conditions (Z. Luo et al., 2015; Sulman et al., 2018). Synthesizing results from perturbation experiments and integrating them into the formation and testing of SOM models are thus key needs (Knapp et al., 2012; Luo et al., 2016), and LTER data can play a central role.

The CZO program is ideally suited to elucidate geologic and landscape controls on SOM as well as the role of soil hydrologic and geochemical traits. For example, clay content has been used as a proxy for SOM stabilization in models for years, yet recent work led by CZO investigators underscores the limits of this approach and the need to better understand and represent integrated soil geochemical controls (Rasmussen et al., 2018). CZO researchers are poised to lead in this area (Heckman et al., 2013; Olshansky et al., 2018), and novel datasets from advanced near-surface geophysical methods and new analytical techniques, combined with unifying conceptual frameworks surrounding hydrologic effects on soil C retention and loss, represent potentially transformative avenues of inquiry. At the landscape scale, SOM process understanding remains limited (O'Rourke et al., 2015). This is an area where CZO datahave contributed new insights intoSOM erosion and deposition (Dialynaset al., 2016; Stacy et al., 2015) and land-water connectivity(Andrews et al., 2011). CZO research integrates across wide temporal scales, from hydrologic responses in seconds to years versus soil weathering and landscape evolution over millennia (Heidari et al., 2017; McIntosh et al., 2017; Riebe et al., 2017). Improved characterization of weathering and erosion rates and associated soil and water residence times can be used to helpbenchmark rates of change observed in SOM models. Because the critical w ne, by definition, extends to the bedrock, CZO sites have and will continue to contribute to SOM insights at depth(Mobley et al., 2015). This is critical given tremendous C pools stored in the subsurface and increasing recognition of the need for vertical resolution in soil C models (Koven et al., 2013).

NEON will enable robust detection of ecosystem change across edaphic and climatic gradients using standardized observations, sensor measurements, and remote sensing. NEON sites monitor SOM along with continuous soil moisture, temperature, and CO_2 fluxes, offering the ability to link soil physical conditions with C dynamics and test assumed linkages applied in many soil modeling approaches (e.g., pedotransfer functions; Van Looy et al., 2017). NEON offers a unique airborne platform that will facilitate scaling of ecological and critical *wne* processes from the pedon to the landscape scale across different eco-climatic domains. For example, high-resolution Light Detection and Ranging (LiDAR) and hyperspectral data can be leveraged to develop new methods for indirect remote sensing of SOM via related ecosystem parameters (Dutta et al., 2015; Mondal et al., 2017). At the other end of the spectrum, NEON is contributing a suite of detailed soil microbial data, including biomass, marker genes, and metagenomic analyses. While the utility of "-omics" data for SOM models is a topic of active debate (Bailey et al., 2017), microbial community traits and life history strategies (rather than community composition per se) are likely to play an instrumental role in fate and stabilization of SOM (Allison, 2012; Fierer et al., 2007; Schimel & Schaeffer, 2012). Innovative approaches for distilling aggregated community traits using metagenomics (sensu Fierer et al., 2014; Leff et al., 2015) may help provide proxies for physiological traits being incorporated into SOM models, such as microbial growth rate, dormancy, and stress tolerance (Georgiou et al., 2017; William R. Wieder, Grandy, et al., 2015). Microbial data from NEON have strong potential to aid in this front.

Taken together, the networks' observational breadth crossing spatiotemporal scales as well as biotic, chemical, and physical gradients can yield novel insights into SOM processes, with implications that span basic research to management and policy making (Figure 1). Moreover, because all of these networks include a long-term monitoring component, they have the potential to shed light on changing SOM dynamics over time with variations in climate, disturbance, and other ecosystem changes (Melillo et al., 2017). This remains a key uncertainty in biogeochemical model projections (Sulman et al., 2018; Tian et al., 2015; Todd-Brown et al., 2014; Wieder et al., 2018). The networks can also facilitate an improved understanding and predictive capacity of SOM heterogeneity *within* sites or watersheds, where broad-scale state factor variation intersects with local-scale variation in soil, organisms, and land surface properties (Bradford et al., 2017). Watershed-scale hydrochemical models have included SOM processes, which will assist such understanding (Bao et al., 2017; Ll et al., 2017). However, the complementary synergies will only emerge with a concerted effort to preserve, share, and leverage network data.

3. Opportunities for Maximizing Network Contributions

While there are many possible benefits to leveraging network data to advance SOM conceptual and numerical models, several important challenges remain. Operationally, the lack of standardized terminology, data collection protocols, and data management strategies makes it difficult to synthesize across networks and integrate cross-disciplinary data sets and findings. Intellectually, it is challenging to unify across scales and ecosystem compartments when applying findings to models (Davidson et al., 2014; Hinckley et al., 2014; O'Rourke et al., 2015). The potential for cross-network collaboration may be hindered when researchers view the same processes through different disciplinary lenses (Richter et al., 2018). Even so, these challenges are surmountable, and we recommend several concrete strategies to catalyze transformative SOM insights from research and observatory network efforts.

First, the networks should mandate and support data dissemination and sharing to facilitate more rapid hypothesis generation, testing, and refinement. SOM data sets should be provisioned in reusable and traceable formats with sufficient metadata to allow others to address questions spanning temporal, spatial, climate, land use, and other gradients. NEON has an advantage here because it was designed as a network of sites with a suite of common measurements, compared to the other investigator-driven networks. LTER has been requiring data sharing for some years and has made significant progress on metadata and data quality. CZO is much younger, and metadata standards have been proposed but not yet universally adopted. Support is needed so that data managers from the networks can create efficient pathways to coordinate data management and dissemination activities, and investigators should consult with them during the data dissemination phase to ensure pathways are working. Adherence to the Findable, Accessible, Interoperable, Reusable (FAIR) data principles would further enhance data discoverability, especially by automated mechanisms (Wilkinson et al., 2016), as would publication in easily accessible repositories such as those that are member nodes of DataONE. Publicly available, cross-network data sets can then be used to help benchmark specific models or processes at specific sites (e.g., Collier et al., 2018; Vereecken et al., 2016). For instance, where available, radiocarbon data can be used to constrain the age of pools and fluxes of SOM

(He et al., 2016), while isotope tracers can shed light on the partitioning ofnew Cinputs into free versus protected fractions (Cotrufo et al., 2015). Such data sets would be very useful in evaluating structural uncertainty among different SOM models (Sierra et al., 2018;Sulman et al., 2018; Wieder et al., 2018). As such , networkSOM data must be discoverable in order to maximize utilitybeyond the initial datacollection effort. Enhanced data dissemination has been shown to benefit both scientific discovery and the researchers who share data in the eddy covariance flux community (Dai et al., 2018). The same will apply for SOM.

Second, the networks should agree to a minimum set ofbaseline SOM measurements that will allow intercomparison of data and results. This should start with measurement of total organic carbon and nitrogen and bulk density (including coarse fragment) across site-specific gradients and with time. Then, networks could add other measurements based on their disciplinary interests (fractions, aggregates, roots, metals, pH, microbial community composition, etc.). Insights from the CZO network could help other networks design protocols for sampling deeper soil depths and considering lateral movement, while the LTER network can provide guidance on protocols and manipulative experiments aimed at capturing effects of biotic interactions, land use history, and disturbance.

Third, the networksshould gobeyond datasharing to promoteactive collaborationsbetween empiricists and SOM modelers(Knappet al., 2012), such that monitoring and experiments are explicitly designed to evaluate model assumptions and models are used to help rule out or confirm mechanisms. Several notable efforts to link data collection, dataharmonization, and modeling are ongoing, including the International Soil Carbon Network, the International Soil Modeling Consorti um, the Community Surface Dynamics Modeling System, and International Soil Radiocarbon Database. These (and others) can provide defined pathways for data collection to advance theoretical understanding and numerical modeling. Collaborative codesign of campaigns to collect empirical data and to develop and test models can serve to bridge these communities but requires investment in new and innovative ways of training students and postdocs to be successful. A movement of fundingagencies toward "convergent science" may provide opportunities and infrastructure to bring modelers and empiricists together.

Lastly, the networks should be test beds for developing new tools, data collection techniques, and models that are particularly promising for improved understanding of SOM dynamics. Examples include the increasing popularity of multiscale geophysical techniques for investigating the shallow subsurface in the CZO network (Parsekian et al., 2015) and the broad application of airborne LiDAR and hyperspectral remote sensing techniques at NEON (Weinstein et al., 2019). Moreover, there are likely to be data-rich nodeswithin the networks that provide opportunities to prototype cross-disciplinary syntheses. The Reynolds Creek Experimental Watershed and CZO site, for example, has data sets that include airborne waveform LiDAR, hyperspectral and geophysical data (Ilangakoon et al., 2018; Mitchell et al., 2015), eddy flux measurements (Fellows et al., 201,8) long-term and high-resolutionsurface climate data(Kormos et al., 2018), landscape-scale SOM and soil inorganic carbon surveys (Stanbery et al., 2017; Will et al., 2017), and detrital input and removal experiments(Lajtha et al., 2018). These data provide unprecedented opportunities to constrain existing models and develop new ones surrounding multiscale controls on SOM. Within-site synthesis at data-rich nodes can also allow for evaluation of the relative importance of different parameters, potentially informing cross-network data collection activities, modeling experiments, and/or coordinated field campaigns.

Although we focus here primarily on U.S.-based ecosystem and CZO networks, we acknowledge that similar networks exist around the globe, and those networks should also be encouraged to collaborate on SOM research and modeling. The International LTER network includes 44 active member networks representing 700 sites across the globe(Mirtl et al., 2018), with variation ranging from highly intensive NEON-like centralized monitoringeffortssuchasTERENO in Germany(Bogena, 2016) to much less intensive and informal groups of sites. Likewise, international networks of CZOs provide immense opportunities to evaluate SOM dynamics along global-scale gradients of environmental change (Banwart et al., 2013).

4. Conclusions

SOM is a key ecosystem property and serves as a point of intersection among data-rich environmental research and observation networks. We can fully leverage network data to improve SOM process understanding and predictions by making it discoverable, comparable, and more tightly coordinated with modeling efforts. One limitation of relying on the networks is that a natu ral gradients approach will not always allow us to attribute variation to particular mechanisms. Nevertheless, the netwo rks ca n accelerate advances in SOM understan ding acrossscales and ecosystems by maintaining open and accessible datasets, taking note of opportunities for targeted experiments and campaigns, promoting close linkages between data collection and modeling efforts (Baatz et al., 2018), an d developing mechanisms to facilitate collaboration and inclusivity among researchers.

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