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### Title

Building bottom-up aggregate-based models (ABMs) in soil systems with a view of aggregates as biogeochemical reactors

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2 **as biogeochemical reactors**

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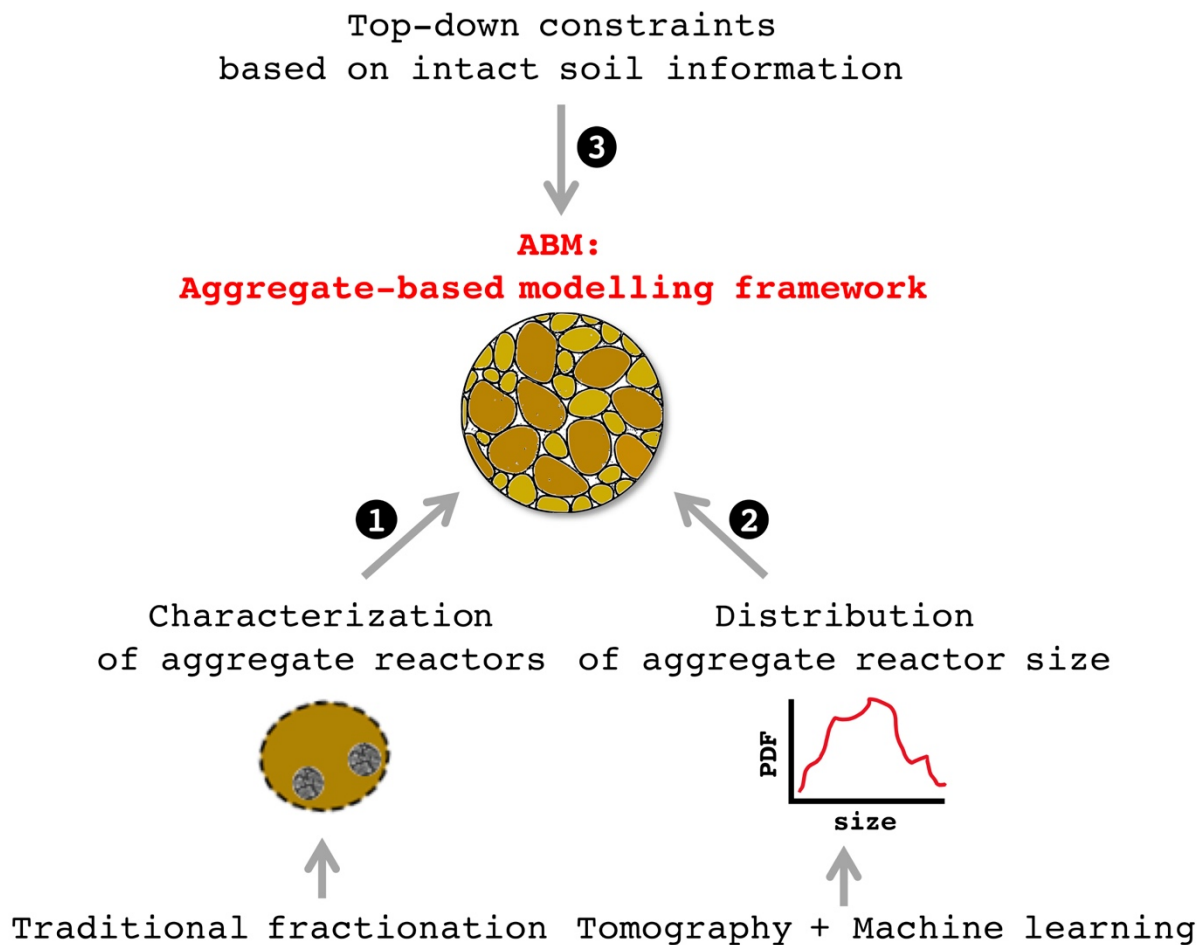
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**Fig.1 Framework for building aggregate-based models (ABMs) in soil systems.** Theories built upon traditional soil fractionation and even artificial aggregates (**Path 1**) and the size distribution of aggregate reactors derived from tomography powered by machine learning (**Path 2**) would inform development of ABMs from the bottom up. This theory can be further constrained by top-down measurements of intact soils through model-data assimilation (**Path 3**).

35           In our recent article in *Global Change Biology* (**Wang et al., 2019**), we proposed to develop  
36 aggregate-based models (ABMs) based on a view of soil aggregates as biogeochemical reactors in  
37 the context of soil heterogeneity. Using a bottom-up philosophy, we argued for developing ABMs  
38 based on a systematic and dynamic view of soils as a constellation of aggregate reactors of different  
39 sizes. We envision that these ABMs offer the potential to bring new mechanistic perspectives into  
40 soil system modelling.

41           In a letter to the editor by **Kravchenko et al. (2019)** an alternative opinion is articulated,  
42 and we appreciate the authors' thoughtful comments. One element of this opinion is that soil  
43 system functioning is not a simple sum of soil constituents—we agree with this statement. Another  
44 objection from **Kravchenko et al.** is primarily based on indeterminacies of size and boundary  
45 conditions of aggregate reactors. We also agree that these limitations are important, and we began  
46 to address them in Section 6 of our article (**Wang et al. 2019**). However, we believe that these  
47 challenges arising from traditional soil fractionation techniques do not necessarily dilute our  
48 confidence in developing ABMs as a prognostic framework that integrates soil processes from the  
49 bottom up. We are grateful to have the opportunity here to further clarify our view and share new  
50 thoughts on it.

51           A bottom-up modelling approach is the 'Holy Grail' of soil system modelling that has been  
52 difficult to achieve because of soil's opaque and heterogeneous nature. In contrast, there has been  
53 a successful infusion of this modelling philosophy into such fields as ecology, sociology,  
54 economics, physics, and others (e.g., **Auyang 1998; Shugart et al. 2018**). In soil science,  
55 aggregates reflect soil system development ('succession'). Aggregates of different sizes form and  
56 collapse constantly during aggregate 'ontogeny', defined by aggregate turnover/stability, while  
57 interacting with many endogenous and exogenous factors. In this context we propose that

58 aggregates, as physically distinct units embedded in the complex soil matrix, can be viewed as  
59 biogeochemical reactors, in which biogeochemical reactions actively transpire and across which  
60 soil macro-pores bridge interactions. By explicitly simulating aggregate reactors of different sizes  
61 along with their interactions, soil system functioning can be quantified as an emergent property of  
62 finer scale processes. This bottom-up modelling philosophy reflects how we understand soil  
63 system composition, structure, function, and dynamics. From this perspective, we firmly believe  
64 that viewing soil aggregates as physically independent units is a way forward for understanding  
65 soil system functioning.

66 In building ABMs, aggregate separation techniques and even artificial aggregates have  
67 played and will continue to play a pivotal role in gaining theoretical understanding of aggregate  
68 reactors and their size-dependent relationships with various factors (**Path 1 in Fig.1**). Aggregate-  
69 based approaches can offer an advantage of measurability relative to current soil carbon models  
70 such as CENTURY for which the simulated carbon pools cannot be measured directly (**Parton**  
71 **1996**). Although building ABMs based on lab-derived aggregate sizes is a good starting point,  
72 **Kravchenko et al.** are legitimately concerned about indeterminacy in real soils. Still, *in-situ*  
73 observations of size distributions of aggregate reactors are possible via tomography techniques  
74 [e.g., X-Ray CT for bulk soil characterization (**Schlüter et al. 2019**) and SEM for finer structure  
75 (**Smith 2008**)] (**Path 2 in Fig.1**). Even more promising are deep learning techniques for image  
76 recognition that can accelerate the retrieval of rich soil structural information from high resolution  
77 soil images derived from these tomography techniques (**Reichstein et al. 2019**). Therefore,  
78 knowledge from traditional soil fractionations and new data on soil structure powered by machine  
79 learning can inform ABM development with aggregate reactors as fundamental units (**Fig.1**).

80           Moreover, top-down constraints based on data from intact soils can further address  
81 shortcomings of the bottom-up approaches (**Path 3** in **Fig.1**). For example, boundary conditions  
82 of aggregate reactors (dependent on inter-aggregate spaces or macro-pores) are hard to determine  
83 because of methodological challenges in conducting *in situ* measurements. Such a lack of *in situ*  
84 information will increase the parameter uncertainty of ABMs. This issue is analogous to the  
85 determination of abiotic environment conditions, such as light intensity, surrounding an individual  
86 tree crown in a diverse forest system, which, though still hard to measure explicitly, do not hinder  
87 explicit model development (e.g., **Wang et al. 2017**). Regarding aggregate reactors, one feasible  
88 and efficient approach would be to calibrate ABMs with data derived from intact soils (**Kennedy**  
89 **and O'Hagan 2001**). Our original article therefore emphasized the utility of top-down experiments  
90 (**Wang et al. 2019**) as also stressed by **Kravchenko et al. (2019)**.

91           In summary, because they are mechanistically and structurally explicit, we argue that  
92 ABMs are a valuable tool for advancing soil system science [see a recent example by **Ebrahimi**  
93 **and Or (2018)**]. Some of the key challenges facing ABMs can be addressed readily with a  
94 combination of theory-driven and data-driven approaches (**Fig.1**). We hope more researchers from  
95 soil science, ecology, data science, and beyond will join in this discussion of developing bottom-  
96 up ABMs by viewing soil aggregates as relatively distinct units. We maintain that biogeochemical  
97 reactors are a useful concept for understanding soil functioning in the context of global  
98 environmental changes.

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