Sensitivity of Process-Based Soil Modelling: The Millennial Model

How sensitive are the output pools in this model to changes in parameters, and what might the effects be for soil organic matter (SOM)?

Lay summary

The increasing accuracy of SOM models has also increased their complexity. Some of the parameters involved in this have little published evidence, but a large effect on the outcomes of the model could lead to large discrepancies in soil organic matter storage forecasts.

Background

There has been a surge of interest in regenerative agriculture since 2015[1]. Commonly mentioned objectives are the restoration of soil health (through increased SOM) and reversal of biodiversity loss[2,3]. Questions remain about how this could be achieved – particularly through combinations of practices, increasing plant diversity and reintegrating livestock into cropping systems[4].

Utilising models allows us to see how these practices might affect SOM into the future. However, widely-used SOM models do not reflect a conceptually current understanding of how SOM cycling occurs. The Millennial Model[5,6], a process-based model with measurable pools (Figure 1), better reflects our increasing understanding of the involvement of microbes in SOM cycling by including second order growth kinetics[7]. This extra complexity comes with an increase in parameters (to 24).

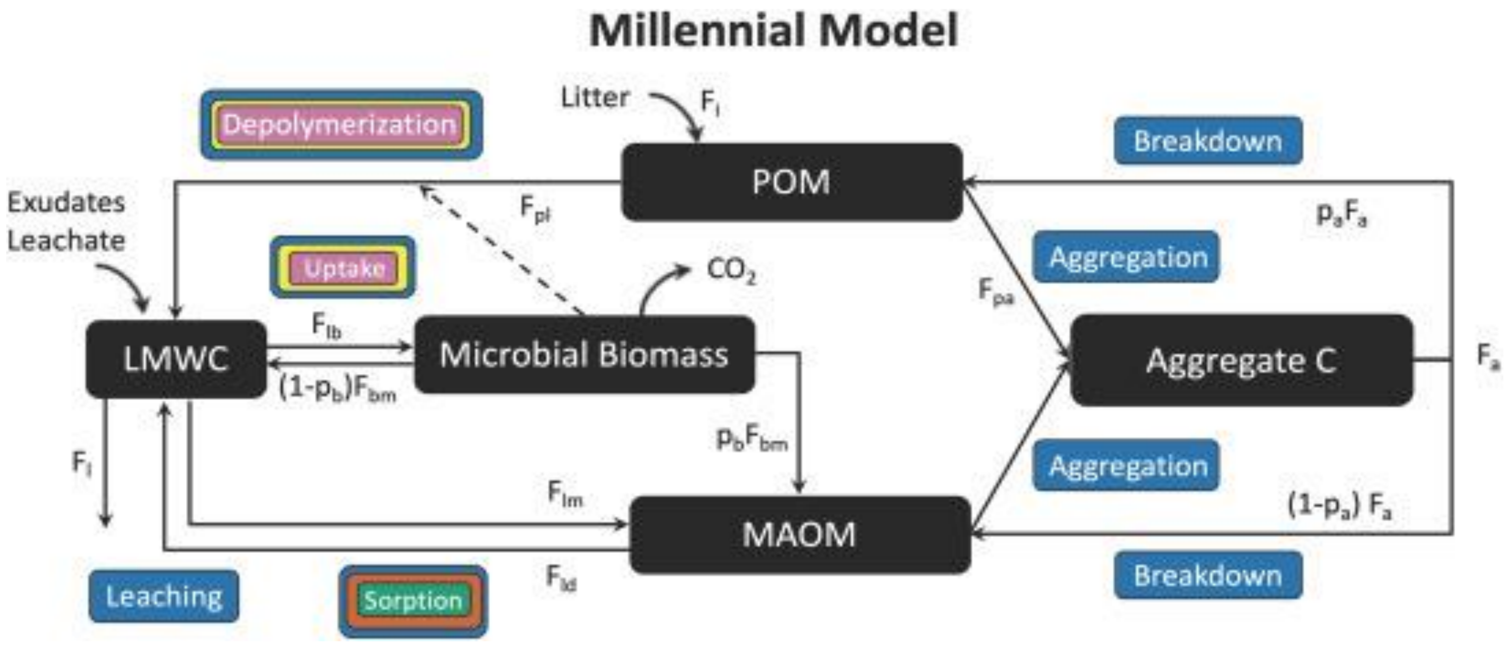

Figure 1. Conceptual diagram of the Millennial Model. Adapted from Abramoff *et al.* (2017 and 2022).

Box 1. SOM pools in Millennial Model.

Particulate organic matter (POM):
- Mostly plant residues, lighter, more complex, more vulnerable to disturbance.

Mineral associated organic matter (MAOM):
- Microbial residues, heavier and less complex, more stable.

Low molecular weight carbon (LWMC):
- Also known as dissolved organic C (DOC) – the portion of SOM in solution. Typically sugars, smaller molecules.

Microbial biomass Carbon (MBC):
- C contained within living soil microbial biomass.

Aggregate C (AGG):
- C contained within soil aggregates.

Methods

Sensitivity analyses are used to determine how variation in the output of a model or system can be attributed to variations in their input parameters.

The analysis involved running the model in R for 100 years, altering each parameter one at a time (100 times) by varying the original parameter value with the rnorm() function with a standard deviation of 20%. The final values for each pool were then extracted and compared with the other parameter variations for each pool.

Results:

Pools

Parameters	MAOM	LWMC	MBC	POM	AGG	CO_2
P_i - Proportion of C input allocated to POM	0.73	1.20	0.63	0.78	0.76	-0.29
P_a - Proportion of aggregate-C breakdown allocated to POM	-1.07	0.02	0.10	0.41	-0.81	1.12
K_{pl} - Half-saturation constant of POM decomposition to LMWC	1.36	0.09	0.02	1.81	-0.43	1.49
A_{pl} - Pre-exponential constant for Vpl	-0.94	-0.06	0.02	-1.06	-0.98	1.05
ϕ - Total porosity	1.24	0.04	-0.03	-0.12	0.28	-0.39
K_{pa} - Rate of aggregate formation from POM	0.04	0.05	0.03	0.03	-1.35	0.36
K_b - Breakdown rate of soil aggregate carbon	0.00	-0.01	-0.00	0.00	0.00	-0.01
P_b - Partitioning of necromass to MAOM and LMWC	1.58	-0.21	-0.01	1.46	1.53	-0.51
K_l - Leaching rate of LMWC	-0.52	0.18	0.02	-0.49	-0.51	0.36
K_{ld} - Specific desorption rate for LMWC and MIC	-0.18	0.05	0.00	-0.17	-0.18	0.10
P_1 - Coefficient for binding affinity for LMWC sorption	1.64	3.06	-0.00	1.50	1.58	-0.50
P_2 - Coefficient for binding affinity for LMWC sorption	-1.47	-1.80	-0.02	-1.44	-1.46	2.68
K_{lb} - Half saturation constant for microbial uptake	1.19	0.63	-0.71	1.34	1.22	-0.26
A_{lb} - Pre-exponential constant for Vlb	-0.94	-0.03	0.04	0.26	0.28	0.59
Λ - Dependence of rate on matric potential	-0.76	-0.66	0.46	-0.83	-0.79	0.79
K_a - Minimum relative rate in saturated soil	-0.05	0.07	0.23	-0.06	-0.05	0.03
ϕ - Matric potential	-0.62	-0.53	0.34	-0.67	-0.63	0.57
K_{bd} - Microbial death rate	0.01	0.01	0.00	0.01	0.01	-0.00
K_{ma} - Rate of aggregate formation from MAOM	0.01	0.01	0.00	0.01	0.01	-0.00
CUE_{ref} - Reference CUE	0.34	0.40	0.01	0.37	0.36	-0.16
CUE_T - CUE dependence on temperature	-0.04	-0.06	0.00	-0.04	-0.04	0.02
T_{ae-ref} - Reference temperature for temp control on CUE	0.24	-0.10	-0.09	0.23	0.24	-0.12

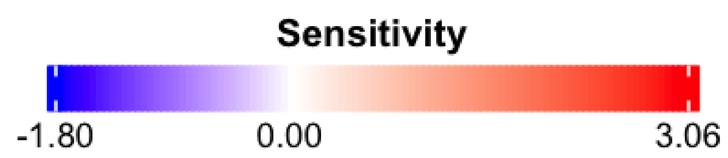

Figure 2. Heatmap showing sensitivity of model output pools and CO_2 emissions to parameters. Sensitivities are calculated as proportional change in output (columns) relative to proportional change in parameter from minimum to maximum value[8]. Key parameters of interest are P_i and P_b.

Discussion

On closer examination, some parameters (notably P_i and P_b) had little published experimental backing. The $\mathbf{P_i}$ parameter is the proportion of C input allocated to POM. P_i is derived from a study on a forest plantation's soils from 1960[9], and is simply 0.5. Given the magnitude of the effect of varying this parameter (Figure 2), the lack of agriculture-specific parameters is concerning. The $\mathbf{P_b}$ parameter (which appears to have no published evidence) is key to the transfer between MBC and MAOM pools. P_bF_{bm} controls MBC → MAOM i.e. how much microbial necromass is portioned to MAOM rather than LWMC. Although theoretically P_b is a key parameter in this process, variation in this parameter in the model does not appear to cause much variation in either of the MAOM and MBC pools. The effects of both K_{lb} and A_{lb} on MBC, CO_2 and MAOM illustrate that increasing the LWMC input does not lead to a bigger microbial biomass pool, but does lead to increased MAOM and decreased CO_2.

Next steps:

- Planning is underway for pot experiments tracing ^{13}C stable isotopes to obtain more realistic data on the P_i parameter in the context of regenerative agriculture.
- This data could enable a Bayesian calibration of the model to these conditions, increasing the accuracy of future predictions.

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