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A SIMPLE SOIL ORGANIC-MATTER MODEL FOR BIOMASS DATA ASSIMILATION IN COMMUNITY-LEVEL CARBON CONTRACTS

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Abstract. Soil carbon (C) sequestration has been proposed as a transitional win–win strategy to help replenish organic-matter content in depleted agricultural soils and counter increases in atmospheric greenhouse gases. Data assimilation and remote sensing can reduce uncertainty in sequestered C mass estimates, but simple soil organic carbon (SOC) models are required to make operational predictions of tradeable amounts over large, heterogenous areas. Our study compared the performance of RothC26.3 and a reduced compartmental model on an 11-year fertilizer trial in subhumid West Africa. Root mean square error (RMSE) differences of 0.05 Mg C/ha between models on total SOC predictions suggest that for contractual purposes, SOC dynamics can be simulated by a two-pool structure with labile and stable components. Faster (seasonal) and slower (semicentennial and beyond) rates can be approximated by constants as instantaneous and infinite decay. In these systems, simulations indicate that cereal residue incorporation holds most potential for mitigation of transient C loss associated with recent land conversion to agriculture.

Key words: carbon sequestration; fertilizer treatments; levels of uncertainty; model simplification; RothC model; soil organic matter; tropics.

Introduction

Soil carbon (C) sequestration has been proposed as a transitional win–win strategy for the next 25–50 years to help replenish organic-matter content in depleted soils of degraded agricultural lands while countering increases in the atmospheric concentration of greenhouse gases, with an estimated 15% offset on current CO_2 emissions (Lal 2007). There is the increasingly popular tool of "contract packages," which are potential contracts between farming communities and carbon-offset buyers (e.g., the World Bank's Prototype Carbon Fund and agencies/NGOs acting on their behalf) in which the communities sell carbon offsets to buyers. In developing countries, contract packages that increase biomass productivity and C returns to the soil could be designed to provide resource-poor "smallholders" (small-scale farmers) with needed incentives to adopt more sustainable land-management practices (Izac 1997, Batjes 2001, Antle and Uehara 2002) when agricultural soil C sequestration becomes an accepted process for the generation of certified emissions reduction (CER) certificates. In fairly uniform environments and across large areas, qualitative changes can be cost-effectively monitored with remote sensing, showing potential for verification of compliant practices such as afforestation, rotation sequences, and fallowing.

However, quantification of relevant biophysical variables such as crop residue by legacy sensors (sensors on the first generation of remote-sensing orbiting satellites) often remains highly inaccurate (Bricklemyer et al. 2007). This is a problem because, at the landscape and community scales amenable to C trade (10–100 Kha), spatiotemporal heterogeneities in production systems deter contractualization on an activity basis (per hectare payments) in favor of contractualization on a mass basis (per ton payments) (Antle and Mooney 2002). This constraint is even stronger in a developing smallholder setting where a variety of relevant factors (e.g., soil texture, choice of crop type, water-table depth) vary over different spatial and temporal scales and interact with eachother, reducing or amplifying overall variability, and further complicating contractual domains characterized by fragmented landscapes and irregular management patterns. Accurate estimation of aggregated soil C on a mass basis presents more complex challenges than the surrogate monitoring of qualitative changes in land use.

Inadequate sampling of the contractual domain is not the only source of uncertainty faced by C mass monitoring. High uncertainty also arises from (1) errors in measurements, which include laboratory methods to "directly" quantify organic C in soil samples (e.g., Walkley-Black [the historical reference method for analysis of soil organic matter]), remote-sensing meth-

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ods to indirectly quantify proxy variables such as standing biomass (e.g., vegetation indices), and (2) errors linked to dynamic C models, including fuzzy and unverifiable structure (e.g., definition of stable fraction), weakly represented processes (e.g., erosion), poorly estimated parameters and initial conditions, and so on. Adequate quantification of uncertainty in sequestered C mass estimates is a prerequisite to contractual verification and compliance enforcement (Vine and Sathaye, 1999).

The nature and relative importance of measurements, models and sampling schemes is likely to vary from project design to implementation, with trade-offs between model complexity and sampling density. When assessing the C-sequestration potential of existing and recommendable practices (design stage), the need to simulate nonlinear processes in the absence of measurements can favor detailed mechanistic plant–SOM (soil organic matter) models such as DSSAT-CENTURY (Gijsman et al. 2002). In contrast, when dealing with C accounting and certification (implementation stage), increased sampling density will take over the task of accounting for nonlinearity in the system and allow for simpler model formulations—particularly suitable for analytical solutions and conversion to continuous form (Parshotam 1996, Andrén and Kätterer 1997, Bolker et al. 1998, Martin 1998, Feng and Li 2001, Fang et al. 2005).

Model simplification is particularly relevant to the study of the dynamics of soil organic carbon (SOC), because the lack of fractionation methods and methodological unification to substantiate turnover-based pool structure (e.g., Shang and Tiessen 2000) can increase uncertainty in model outputs (Larocque et al. 2006). Under such conditions, total SOC prediction is clearly more an issue of formulation tractability and ease of computation (Bolker et al. 1998) than a problem of potential physical, chemical, or biological conceptualization.

This paper examines one such simplification by comparing the performance of the five-pool Rothamsted soil-carbon turnover model (RothC) with a simpler compartmental model proposed for stochastic satellite and ground data assimilation (after Bostick et al. 2007). We hypothesize that (1) RothC's HUM (humified organic matter) slow pool can be considered stable over a 20-year contractual period, allowing for a consolidation of RothC's HUM and IOM (inert organic matter) components into a single stable pool; (2) a yearly time step will not significantly affect a model's ability to simulate short-term C dynamics for trading purposes; (3) there is no significant difference among crops in terms of their residue decomposition rates on annual time scales, allowing for reduction of RothC's DPM:RPM ratio of fresh biomass (the ratio of decomposable plant material to resistant plant material) into a constant. Total soil organic C estimated by each approach is compared with field data from an 11-year rotation experiment in the subhumid tropics of West Africa. Results are discussed from a model-simplification perspective motivated by issues of timescale relevance, data scarcity, and information uncertainty. Available data do not allow for a more comprehensive assessment of the net CO_2 equivalent effect in these systems. This study pertains only to the development of operational monitoring and certification subsystems for putative C-sequestration contracts in smallholder agricultural communities.

Materials and Methods

Reference model selection

Many models of soil organic matter (SOM) turnover have been developed (McGill 1996). In a nine-model comparison exercise, Smith et al. (1997) found no significant difference in performance across models intended for arable crops. Most SOM models are compartmental, with mass fluxes between conceptual pools often expressed as first-order kinetics. This allows for robust functionality, but usually involves some degree of empiricism and a weaker representation of real-world processes. Cohort models are arguably more realistic as they mechanistically simulate trophic decomposition by microbial biomass, responses to transient vegetation, and coupled N and C dynamics, but are complex and difficult to parameterize (Gignoux et al. 2001). In fact, moving away from traditional pool-based modeling paradigms involves considerable difficulties (Thornley and Cannell 2001). Our rationale for choosing a reference model followed three criteria: (1) it should be a stand-alone model, hence drivable by either biomass predictions or measurements, (2) it should be structurally simple, allowing for straightforward simplification and easy parameterization, and (3) it should have been favorably evaluated over a range of representative agroecological conditions.

As the most frequently reported models in simulation studies of soil C dynamics, CENTURY (Parton et al. 1988) and RothC (Jenkinson and Rayner 1977) often serve as reference test beds for other modeling work. They represent extremes in a range of complexity and accessibility (FAO 2004) and have been historically evaluated in a variety of environments. Of these two, CENTURY has been adapted for mechanistic crop-biomass prediction (Gijsman et al. 2002) and used for stochastic soil C-predictions, but its complexity makes it less amenable to utilization in data-scarce regions (Zimmerman et al. 2005, Koo et al. 2007). Hereafter used as a reference model, RothC version 26.3 (Coleman and Jenkinson 1999) features four active soil organic-carbon pools plus one inert organic matter (IOM) compartment. Fig. 1 represents fluxes and partitioning of carbon from plant residue (PR) and farmyard manure (FYM) to the four active compartments: Decomposable plant material (DPM), resistant plant material (RPM), microbial biomass (BIO) and humified organic matter (HUM), alongside the IOM. Compartment shapes are

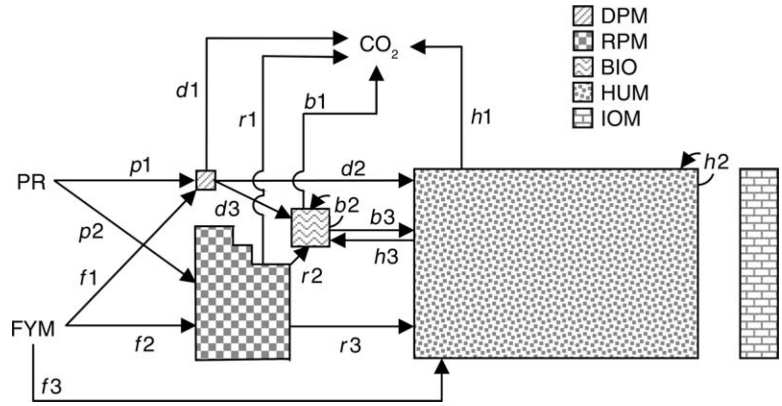

FIG. 1. C pools and fluxes and the linear system of equations in the RothC model (adapted from Coleman and Jenkinson [1999]). Key to abbreviations: DPM = decompostable organic material, RPM = resistant plant material, BIO = microbial biomass, HUM = humified organic matter, and IOM = inert organic matter:

$$\begin{aligned}
\mathrm{BIO}_{t+1} &= \mathrm{BIO}_t + (b2 + d2 + r2 + h3 - b1)\Delta t\\
\mathrm{HUM}_{t+1} &= \mathrm{HUM}_t + (h2 + d3 + r3 + b3 + f3 - h1)\Delta t\\
\mathrm{DPM}_{t+1} &= \mathrm{DPM}_t + (p1 + f1 - d1 - d2 - d3)\Delta t\\
\mathrm{RPM}_{t+1} &= \mathrm{RPM}_t + (p2 + f2 - r1 - r2 - r3)\Delta t\\
\mathrm{IOM}_{t+1} &= \mathrm{IOM}_t
\end{aligned}$$

where b, d, r, and h refer, respectively, to fluxes of carbon originating in the BIO, DPM, RPM, and HUM pools, f refers to inputs of carbon from farmyard manure (FYM), and t refers to time.

roughly proportional in dimension to relative pool sizes reported in the literature.

Simplification into a two-pool model

HUM completely decomposes over periods of about 50 years. Neither DPM (<1 yr) nor BIO (<2 yr) alone wield a dominant effect on soil organic carbon (SOC) variations over time periods of less than 20 years. In fact, the initial value of both DPM and BIO is negligible as they reach equilibrium within 12 months (Janik et al. 2002). Such is not the case with HUM, which can account for up to 75% of total soil organic carbon (Coleman and Jenkinson 1999) and which requires accurate initial estimates given a low decomposition rate. Janik et al. (2002) further observe that RPM constitutes the largest contributing factor to modeled soil C among initial pool sizes (HUM and IOM being the lowest). With HUM assumed as the difference between total SOC and the sum of IOM and RPM, this eventually stresses the significant effect of both HUM and RPM initial values. Although the relatively small IOM appears to exert a moderate influence on total SOC, considerable ranges of variation are cited (e.g., Tate et al. 1995, Falloon et al. 1998), from 1.1% to 25.6% of total SOC, warranting accurate specification as well (Skjemstad et al. 1996, Falloon et al. 2000). In practice, IOM allows the separation of centennial from millenial C, both beyond the time horizon of a C-sequestration contract.

Thus, RothC's structure holds obvious incentives for simplification to monitor C dynamics on intermediate timescales amenable to C trade. Following Bostick et al. (2007), a simplified, yearly time-step model is proposed, with a labile and a stable pool (Fig. 2). The labile compartment L is analogous to RothC's RPM. The stable compartment S roughly corresponds to the sum of RothC's HUM (dominant) and IOM (smaller) pools. With residency time on the order of a year or less, DPM and BIO material can be approximated as a quasi-direct CO_2 release rate r ($f1 + p1$ in RothC), and corresponding pools can be neglected on a yearly time step. Furthermore, all C fluxes to and from stabilized C are considered negligible on contractual timescales. These include CO_2 release, direct inputs from farmyard manure (2% only in RothC, with limited farmyard manure applications in smallholder agriculture anyway), and transfers between the stabilized and the labile compartments. Biomass and farmyard inputs reach L with rate i ($f2 + p2$ in RothC), and L decomposes with rate k ($r1$ in RothC).

The rationale for a two-compartment model follows. The great differences in SOM ages measured by carbon dating require a partitioning of biologically resistant and susceptible material (Jenkinson 1990) that single-component models cannot really capture (Fang et al. 2005). Simple two-compartment models have been successfully used to represent SOC dynamics over time spans of a few years to centuries, with a fast pool humifying into a slow pool, allowing for use by nonspecialists, analytical solutions, and easier parameterization (Andrén and Kätterer 1997, Thornley and Cannell 2001, Kirschbaum 2004). Testing the ICBM (introductory carbon-balance

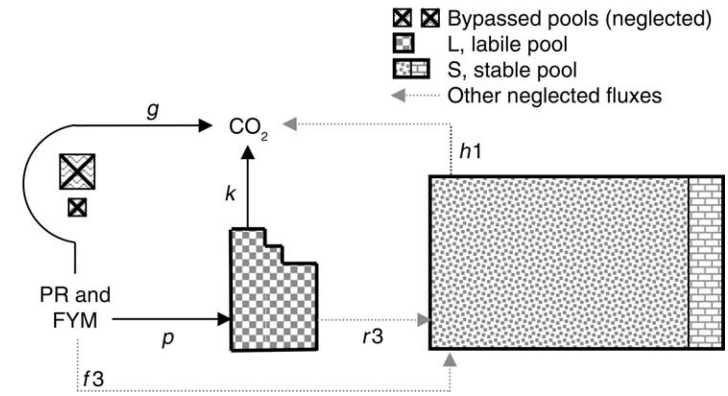

FIG. 2. C pools and fluxes and the linear system of equations in the simplified two-pool model (in analogy to the RothC representation in Fig. 1). In the figure: g = the "direct" release of carbon as CO_2 by plant residues (PR) and farmyard manure (FYM) (not transiting by any pool in the model); k = the release of carbon by the labile pool (L); $h1$, $f3$, and $r3$ correspond to carbon fluxes in RothC (Fig. 1) that are neglected in the two-pool model (Fig. 2); and p refers to inputs of carbon from plant residue (as in Fig. 1):

$$L_{t+1} = L_t + (p - k)\Delta t$$
$$S_{t+1} = S_t.$$

model) soil-carbon model dynamics and parameter sensitivity, Andrén and Kätterer (1997) note that two fractions decomposing, respectively, every 1.25 and 165 years are probably not enough to simulate tropical, slow SOC dynamics. Within limited time periods, they suggest a non decomposable fraction. The proposed model follows these heuristic approaches, with some differences that include (1) a constant, stand-alone fraction containing centennial turnover material (with assumed infinite turnover time inside contractual timeframes), (2) a labile (slow) fraction with decay rate k corresponding to decadal turnover times, and (3) a yearly time step resulting, as a first approximation, in the elimination of the traditional fast pool, host to annual turnover material (and, consequently, that of the associated DPM:RPM ratio).

Experimental data and site description

Both RothC version 26.3 and the simple two-pool model were run and calibrated using biomass, SOC, and nearby weather measurements from a 1993–2003 fertility management experiment in Farako-Ba, Burkina Faso (11.09° N, 4.32° W; northern Guinean agro-ecological zone) with 56 combinations of crop-rotation sequences and input levels. Crops included cotton (*Gossypium hirsutum* L.), groundnut (*Arachis hypogaea* L.), maize (*Zea mays* L.), and sorghum (*Sorghum bicolor* (L.) Moench). Fertilization involved eight input levels with control, PK, NPK, NPK + dolomite (D), PK + crop residue, NPK + crop residue, PK + compost (CP), and PK + manure (MN) treatments. The experiment was installed on a loamy sand soil with 74% sand and 7% clay (estimated bulk density: 1.46 g/cm^3) after a six-year native grass fallow (Bado 2002). Standing biomass data were collected every year (four replicates/combination) and used to prescribe biomass inputs to the models. A total of 132 SOC measurements (0–20 cm; four replicates except in 2001: three replicates) were available for calibration purposes from a subset of five rotations: continuous cotton (1998, 2003), continuous groundnut (2001), continuous sorghum (1998, 2001, 2003), groundnut–sorghum–cotton (1998, 2001), and cotton–maize–sorghum (2003), and four input levels (control, NPK, NPK+ D, and PK + MN). Crop-residue treatments involved the incorporation of standing-biomass residues in the soil. Other treatments did not receive residue, and the root system was the sole plant source of C inputs. A detailed description of the experiment is available in Bostick et al. (2007).

Parameter estimation

Experimentation with RothC v. 26.3 and a sensitivity analysis by Janik et al. (2002) provided a list of important parameters to estimate with associated ranges of variation (Table 1). Similar values for the simplified two-pool model are also mentioned (after Bostick et al. 2007). Model parameters were estimated with a simplex generalized reduced gradient nonlinear optimization in Microsoft Excel Solver (Fylstra et al. 1998). Initial system states (pool sizes) were optimized alongside the decomposition rate and crop specific DPM:RPM ratio parameters, hence a total of five initial states U_0 and five parameters θ for RothC (two-pool model: two U_0, two θ). For RothC, the optimization algorithm was subject to two range sets for all parameters and initial states: nominal value ±30% (set 1), ±60% (set 2), normal distribution assumed, with initial total SOC constrained to the measured value (16.5503 Mg C/ha). The cost function sought to minimize the sum of squared differences between combined simulated pools (SOC_i) and total measured (Z_i) carbon:

$$\text{minimize } SS(\theta, U_0) = \sum_{i=1}^{n} (SOC_i - Z_i)^2. \qquad (1)$$

Initial states and decomposition rates were first optimized across all treatments ($n = 132$), then optimization procedures were re-run to include DPM:RPM ratios on individual continuous cropping rotations only (cotton, $n = 32$; groundnut, $n = 12$; sorghum, $n = 44$). Additionally, different parameterization options were explored for the RothC model: optimization of all five initial states vs. three dominant ones only (RPM, HUM, IOM), optimization of all four decay rates vs. the dominant one only (k_{RPM}), no rate optimization at all, and combinations of the above.

TABLE 1. Summary list of RothC and two-pool model parameters optimized for the Farako-Ba (Burkina Faso) long-term fertility-management experiment.

Initial state U_0, parameter θ	Nominal†	Set 1 Minimum −30%	Set 1 Maximum +30%	Set 2 Minimum −60%	Set 2 Maximum +60%
RothC model					
Initial relative pool size (% of initial total SOC)					
DPM	0.5	0.35	0.65	0.2	0.8
RPM	14.5	10.15	18.85	5.8	23.2
BIO	2	1.4	2.6	0.8	3.2
HUM	75	52.5	97.5	30	100
IOM	8	5.6	10.4	3.2	12.8
Decay rate, k (yr^{-1})					
k_{DPM}	10	7	13	4	16
k_{RPM}	0.3	0.21	0.39	0.12	0.48
k_{BIO}	0.66	0.462	0.858	0.264	1.056
k_{HUM}	0.02	0.014	0.026	0.008	0.032
DPM:RPM	1.44	1.008	1.872	0.576	2.304
Two-pool model					
Decay rate, k (yr^{-1})					
k	0.33	0–1‡			
Initial relative pool size (% of initial total SOC)					
Labile compartment, L	43.6	0–100‡			
Stable compartment, S	56.4	0–100‡			

Notes: There are two sets of range values. In range set 1 (RothC), acceptable value ranges are determined as the nominal value ±30% (range set 2: ±60). Key to abbreviations: SOC = soil organic carbon; DPM = decompostable organic material, RPM = resistant organic material, BIO = microbial biomass, HUM = humified organic material, and IOM = inert organic material.

† Nominal values for RothC model are after Janik et al. (2002); for two-pool model, Bostick et al. (2007).

‡ Minimum and maximum values for the two-pool model are for the entire model and are not divided into ranges.

Comparative evaluation of models

After parameter and initial-condition estimation, optimized values were used to simulate SOC. RothC and the simplified two-pool model were propagated forward in time for all individual replicates of all combinations of seven crop rotations and eight fertilizer levels. In RothC, soil was covered by vegetation from sowing month to harvest month. The two-pool model was also run on a monthly time step to look separately at the effects of simplification in structure (first hypothesis) and time (second hypothesis).

Where SOC measurements were available, their outputs were compared with measurements using mean bias error (MBE), root mean square error (RMSE) and lack-of-fit (LOFIT) statistics with associated F and t significance values (for LOFIT and RMSE). The purpose was to highlight any potentially significant discrepancy with measurements following Smith et al. (1997). As delineated in the following notations, each of the 20 combinations of rotations and levels was taken as a distinct experiment featuring o_{ij} measurements on $i(1 \cdots N)$ dates and for $j(1 \cdots n)$ replicates. Similarly, p_{ij} refer to model predictions for the ith date and jth replicate, and $\bar{o}_i$ is the average of replicate measurements for the ith date. Aggregate statistics were also calculated (rotation-wise, level-wise, and overall). Formulas are provided at the experiment level.

Mean bias error (Willmott 1982) is the average difference between measured and simulated values, and negative (positive) differences indicate under- (over-) prediction by models:

$$\mathrm{MBE} = (Nn)^{-1}\sum_{i=1}^{N}\sum_{j=1}^{n}(o_{ij} - p_{ij}). \tag{2}$$

The root mean square error (Willmott 1982) eliminates compensation between under- and over-prediction. Standard errors of measurements were computed from replicate values to assess RMSE's statistical significance at $P = 0.05$ (two-sided Student's t test):

$$\mathrm{RMSE} = \left[(Nn)^{-1}\sum_{i=1}^{N}\sum_{j=1}^{n}(o_{ij} - p_{ij})^2\right]^{0.5}. \tag{3}$$

The lack-of-fit statistic (Whitmore 1991) separates measurement and model errors present in the residual sum of squares. Its significance was computed at $P = 0.05$ (one-sided Fisher F test):

$$\mathrm{LOFIT} = \sum_{i=1}^{N} n_i(\bar{o}_i - p_{ij})^2. \tag{4}$$

Focused on inorganic-fertilizer effects, the Farako-Ba experiment did not include SOC measurements on 36 of the 56 treatments, including those with crop-residue incorporation. The latter were thus useless for model calibration but provided valuable biomass data to simulate SOC trends and check whether the two-pool model followed RothC's response. To that purpose, the difference between total predictions by the two models

TABLE 2. Optimized values for U_0 initial states 3 and 5 (carbon pools) and θ parameters 0, 1, and 4 (decay rates) for two value-range sets (±30%, ±60% of nominal value, n.v.).

			Initial states					Decay rates				
U_0	θ	Range ±% n.v.	DPM	RPM	BIO	HUM	IOM	k_{DPM}	k_{RPM}	k_{BIO}	k_{HUM}	RMSE
5	0	30	0.11	3.12	0.43	11.97	0.93	*10.00*	*0.30*	*0.66*	*0.02*	1.61
5	1	30	0.11	3.12	0.43	11.97	0.93	*10.00*	0.39	*0.66*	*0.02*	1.56
5	4	30	0.11	3.12	0.43	11.97	0.93	7.00	0.39	0.86	0.03	1.45
3	0	30	*0.00*	2.98	*0.00*	12.30	1.27	*10.00*	*0.30*	*0.66*	*0.02*	1.94
3	1	30	*0.00*	3.12	*0.00*	12.50	0.93	*10.00*	0.39	*0.66*	*0.02*	1.76
3	4	30	*0.00*	3.12	*0.00*	12.50	0.93	7.00	0.39	0.86	0.03	1.50
5	0	60	0.17	3.84	0.53	11.49	0.53	*10.00*	*0.30*	*0.66*	*0.02*	1.41
5	1	60	0.17	3.84	0.53	10.81	1.21	*10.00*	0.43	*0.66*	*0.02*	1.41
5	4	60	**0.17**	**3.84**	**0.53**	**11.49**	**0.53**	**4.00**	**0.43**	**0.82**	**0.02**	1.40
3	0	60	*0.00*	3.84	*0.00*	12.18	0.53	*10.00*	*0.30*	*0.66*	*0.02*	1.54
3	1	60	*0.00*	3.84	*0.00*	12.18	0.53	*10.00*	0.48	*0.66*	*0.02*	1.47
3	4	60	*0.00*	3.84	*0.00*	10.59	2.12	4.00	0.47	0.78	0.03	1.44

Notes: When only a subset of states are optimized, BIO = DPM = 0. When only one parameter is optimized, it is k_{RPM}. Cells with italic data refer to fixed (nominal) values (n.v.). Boldface values are subsequently used in the forward runs. RMSE = root mean square error; for other acronyms see Table 1 notes.

was also used as an indicator of their potential concordance or discrepancy.

RESULTS

Initial pool sizes and turnover rates

Estimated RothC parameters and initial states changed consistently across optimization options, yielding better soil organic carbon (SOC) predictive quality when more initial states and decay rates were allowed to vary over a wider range around nominal values. Overall root mean-square error (RMSE) varied from 1.94 to 1.40 Mg C/ha (Table 2, Fig. 3). Forcing DPM (decompostable plant material) and BIO (microbial biomass) initial values to 0 inevitably increased HUM (humified organic matter) and IOM (inert organic matter) with no effect on rates, and a loss of predictive skill. Rate optimization always resulted in reduced DPM turnover (yet always quarterly or faster) and augmented resistant plant material (RPM) and microbial biomass (BIO) decay, with an increase in prediction skill. Relaxing the range of acceptable values improved agreement with SOC measurements through increased RPM, DPM, BIO, RPM decay rate (k_{RPM}) and reduced DPM decay rate (k_{DPM}) with no effect on other rates and initial states.

Retained initial pool sizes of 0.17, 3.84, 0.53, 11.49, and 0.53 Mg C/ha (1, 23, 3, 70, and 3% of total SOC, respectively; Table 3) for DPM, RPM, BIO, HUM, and IOM, respectively, are generally consistent with published values for comparable agro-ecological conditions. Slow and passive (refractory) pools being the most significant for C sequestration, in RothC we are

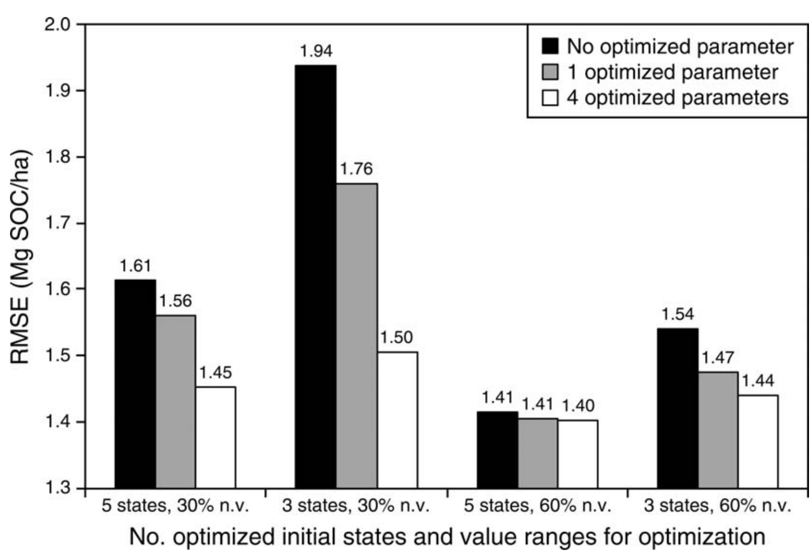

FIG. 3. Evolution of total soil organic carbon (SOC) predictive quality (measured by the root mean-square error, RMSE) as a function of the number of RothC initial states and number of parameters considered for optimization, for two value-range sets; n.v. = nominal value.

TABLE 3. Optimized model parameters and initial states used to simulate the Farako-Ba (Burkina Faso) fertility-management experiments.

	Initial states (Mg C/ha)							Decay rates, k (yr^{-1})					
Model	DPM	RPM	BIO	HUM	IOM	L	S	k_{DPM}	k_{RPM}	k_{BIO}	k_{HUM}	k_L	RMSE
RothC	0.17	3.84	0.53	11.49	0.53			4.00	0.43	0.82	0.02		1.40
Two-pool						7.32	9.23					0.214	1.46

Note: Key to column headings: L = labile pool, S = stable pool, k_L = decay rate of the labile pool; see Table 1 for key to other abbreviations.

primarily interested in HUM and IOM. Falloon et al. (1998) report 0.7 Mg C/ha IOM (3.5% of total SOC) in the Ho-Keta savanna plains of Ghana, and a range of 1.9–9.8% of total SOC for a set of tropical sites. The relative discrepancy between combined HUM + IOM value (73% of total SOC) and refractory SOM pool sizes (13–59%) as reported by Falloon and Smith (2000) relates to differences in pool age between models (HUM in RothC: "only" 50 years), and plausible differences in overall soil C dynamics. While refractory SOM is, strictu senso, limited to IOM in RothC, it could as well be the sum of IOM + HUM for our purposes. Optimized values for the stable pool in the two-compartment model is 9.23 Mg C/ha (Table 3), identical to earlier results on the Farako-Ba site (0.32% of SOC on a mass basis; Bostick et al. 2007).

Turnover rate constants in RothC were originally set using long-term Rothamsted (UK) experiments and are normally not altered (Coleman and Jenkinson 1999). However, the nonbinding, conceptual nature of C compartments and potential differences between C dynamics at Rothamsted and in the Tropics suggest that alteration may be useful. In fact, a number of RothC application studies (e.g., Jenkinson et al. 1999, Janik et al. 2002, Diels et al. 2004) have experimented with variable decay rates. Fig. 3 shows that with the Farako-Ba data set, rate optimization can reduce RMSE on total SOC predictions by as much as 0.44 Mg C/ha when the three larger C pools (BIO, HUM, RPM) only are optimized (0.16 Mg C/ha when all five C pools are optimized). Optimization of the single most influential rate (k_{RPM}) in addition to three pools improved RMSE by 0.18 Mg C/ha (with five pools: 0.05 Mg C/ha). Given data constraints and the subsequent multiple solutions to the estimation problem, retained rate coefficients (4, 0.43, 0.82, and 0.02) for k_{DPM}, k_{RPM}, k_{BIO}, and k_{HUM}, respectively, are reasonably close to recommended values. The decreased decay rate for the small DPM pool wields a limited influence on total SOC prediction after 10 years even for acid soils (Jenkinson et al. 1999), much like the DPM:RPM ratio on which it depends (see next section). In the two-pool model, the unique k_L decay rate is optimized at 0.21 yr^{-1}, fairly distinct from an earlier estimate of 0.33 yr^{-1} by Bostick et al. (2007). This disparity might result from different treatment of abcised material (estimated in the former study, and neglected here), possible minor differences in the measurement sets used for calibration purposes, and optimization setup, but could not be ascertained.

DPM:RPM ratio in RothC

Including the DPM:RPM ratio in the set of adjustable parameters yields a maximum effect on total SOC prediction in the order of 0.1 Mg C/ha when the ratio is allowed to vary from 0.25 to 3.35, and there is no perceptible difference between cotton, groundnut, and sorghum. The ratio has some effect during the first two years of litter decomposition, and becomes rapidly negligible afterwards with limited influence on RothC (Janik et al. 2002, Diels et al. 2004, Shirato and Yokozawa 2006). In crop management for C sequestration (excluding agroforestry), there is no need for dynamically decoupling fast decay rates, and the DPM:RPM ratio can be approximated by a constant C-release rate.

Predictive performance of models

Table 4 illustrates the close predictive performance of both models, which display the same bias pattern including systematic SOC underestimation in the PK + MN (P–K–manure [MN]) level and continuous groundnut rotation. RMSE varies identically in both models with some significant departures from observations in the sorghum continuous rotation and PK + MN fertilizer level, and only five statistically significant differences between model lack of fit (LOFIT) can be reported across 20 treatments, when compared to observations. Most discrepancies with measurements and between models are observed in treatments involving sorghum, which is probably the experiment's most heterogenous crop, notably at the root system level (sole contributor to control, NPK, NPK + D [dolomite], and PK + MN treatments). Beyond similarities in performance by the two models, these statistics illustrate the uncertainty inherent in SOC measurements. This is most notable in the sorghum continuous rotation, where simulated SOC fails to fall within the interval defined by the mean and standard deviation of measurements in 1998. Drawn from 16 soil samples (4 treatments × 4 replicates), the values (0.33 ± 0.04% [means ± SD] on a soil mass basis) look like outliers and might have been affected by laboratory or reporting errors. Some replicate values have been observed in SOC measurements across repetitions inside the data set, and exploratory suppression of replicate values in the 1998

TABLE 4. Model performance statistics by crop rotation and fertilizer-treatment level.

	Rotations‡					
Treatment†	CCC	CMS	GGG	GSC	SSS	All
Bias statistic						
RothC model						
Control	0.34	1.15	−0.57	0.56	1.41	0.76
NPK	0.00	0.50	−1.90	0.02	1.11	0.26
NPK + D	−0.11	0.61	−0.74	0.33	−0.05	0.03
PK + MN	−1.08	−0.48	−1.09	−0.29	−0.74	−0.73
All levels	−0.21	0.44	−1.08	0.16	0.43	0.08
Two-pool model						
Control	0.53	1.39	−0.78	0.26	1.18	0.68
NPK	0.19	0.77	−2.11	−0.27	0.40	0.03
NPK + D	0.09	0.89	−0.93	0.05	−0.25	−0.03
PK + MN	−0.82	−0.15	−1.29	−0.57	−1.52	−0.96
All levels	0.00	0.73	−1.28	−0.13	−0.16	−0.07
Root mean square error, RMSE						
RothC model						
Control	1.31	1.21†	1.35	0.92	1.59	1.34
NPK	1.49	1.60	2.51	1.22	1.56†	1.60
NPK + D	1.09	1.64	0.79	0.75	1.29	1.16
PK + MN	1.68†	0.91	1.65	1.25	1.59†	1.49
All levels	1.41	1.37	1.69	1.05	1.51	1.40
Two-pool model						
Control	1.38	1.44†	1.45	0.23	1.40	0.75
NPK	1.50	1.71	2.67	1.22	1.59†	1.64
NPK + D	1.08	1.76	0.97	0.65	1.28	1.17
PK + MN	1.53†	0.78	1.79	1.34	2.14†	1.68
All levels	1.38	1.44	1.83	1.03	1.65	1.46
Lack of fit, LOFIT						
RothC model						
CTRL	1.05	5.14‖	0.87	3.50	24.28‖	34.84‖
NPK	0.38	1.07	10.64	4.06	22.27‖	38.41
NPK + D	0.57	1.09	1.64	1.83	6.49	11.62
PK + MN	16.64‖	0.87	3.47	1.48	25.01‖	47.47‖
All levels	18.63	8.17	16.63	10.87	78.05‖	132.35‖
Two-pool model						
Control	2.43	7.54‖	1.72	1.43	18.00	31.12‖
NPK	0.50	2.53	13.11	4.09	23.25	43.49‖
NPK + D	0.43	2.73	2.60‖	0.89	6.21‖	12.85
PK + MN	12.94‖	0.00	4.89	3.10	47.25	68.18‖
All levels	16.30	12.80	22.32	9.51	94.70‖	155.63‖

Note: All units are Mg C/ha.
† MN = manure.
‡ CCC = continuous cotton, CMS = cotton–maize–sorghum, GGG = continuous groundnut, GSC = groundnut–sorghum–cotton, SSS = continuous sorghum.
§ Simulated values are outside 95% confidence interval of measurement sample.
‖ Error in simulated values is significantly larger than error in measurements at $P = 0.05$.

continuous sorghum-rotation case allows the measured SOC value to rise to 0.35 ± 0.04% on a soil mass basis. Overall, RothC predicted final total SOC with a relative RMSE of 13.8% (two-pool: 14.0%), comparable with the 12.5% figure of Bostick et al. (2007).

A closer look at two-pool model predictions shows that they are always equal or higher than RothC's in the range of 0–0.02% of soil mass after each C input pulse (0 to ~0.6 Mg C/ha or ~5% of current total SOC) for all treatments with limited exceptions in the cotton–maize–sorghum rotation, and they display two variability modes on seasonal and decadal time scales. Seasonal differences are an artifact of the different time resolutions and the assumption that residue C inputs to the soil occur in December (just after harvest), bringing about a higher concordance between models at that time of the year (Fig. 4). The tendency of the two-pool model to predict a shallower SOC decline in the first half of the experiment period results from both the model structure (more rigid) and the lack of SOC measurements to better constrain the fit during the first years. The local inversion of the difference in the cotton–maize–sorghum treatment (Fig. 4d) corresponds with high C input following maize (2000) and sorghum (2001) cultivation. Here again, the two-pool model lacks flexibility, but responds with a noticeable inflection of the SOC loss

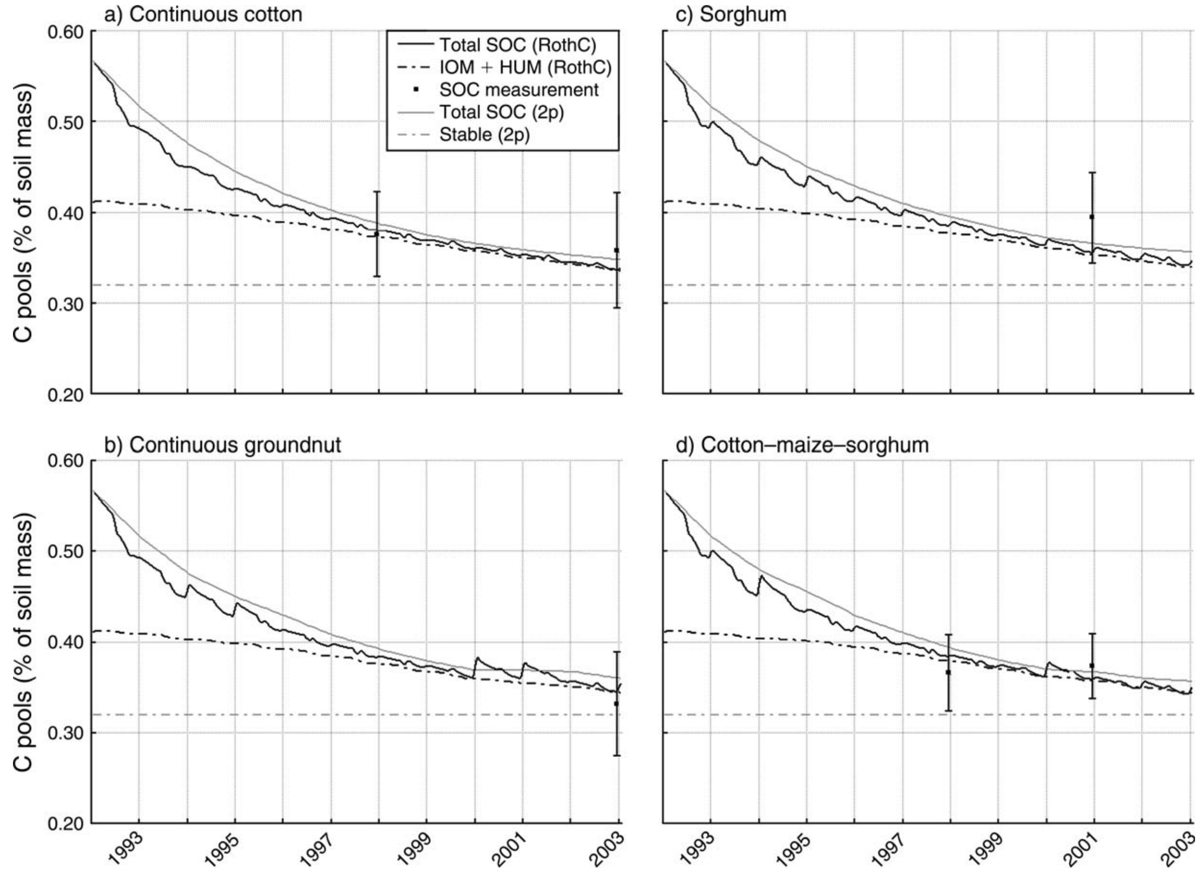

FIG. 4. Total and stable SOC content (%) simulated by RothC and a yearly two-pool (2p) model. Error bars represent ±SD from measurements mean.

curve. At the end of the simulation period, differences between models stand below 0.01% of soil mass (~0.3 Mg C/ha or ~3% of final total SOC).

SOC trends over contractual timescales

Figs. 4 and 5 illustrate the transient C-loss stage associated with agricultural disturbance following steady-state conditions (Batjes 2001, Post et al. 2001). The characteristic effect of initial cultivation is clearly more drastic than subsequent management practices (Christensen 2001). Observed and modeled decay (in the order of 25–40% over 11 years) concur with other values from the literature. Simulated final SOC (9.9–10.5 Mg C/ha) corresponds to values observed by Batjes (2001) on cultivated luvic arenosols in Senegal. In a 16-year continuous maize–cowpea control rotation in subhumid Ibadan, Nigeria, Diels et al. (2004) observed a 50% loss in total SOC, fast enough to require a doubling of all decomposition-rate constants in RothC (compared to nominal values). A similar trend is visible in our results (30–50% increase in k_{RPM} rates from nominal values).

Crop-residue treatments (Fig. 5: right-hand side) illustrate the remarkable contribution of residue incorporation to SOC dynamics. Rather limited in cotton and groundnut, they substantially offset C loss in cereal systems (Table 5) with limited SOC decay of 25–33%. Diels et al. (2004) noted that a mitigating 8.5 Mg dry matter$\cdot$ha$^{-1}\cdot$yr^{-1} application of crop residue (CR) would still result in a 25% loss over the same period, which is consistent with our prediction for the PK + CR and NPK + CR treatments. This is somewhat more moderate than our simulated decay of 36–39% (continuous cotton), 32–33% (continuous groundnut), 26–33% (continuous sorghum), 26–30% (cotton–maize–sorghum and groundnut–sorghum–cotton) on the Farako-Ba residue treatments, where residue input was also smaller. Effects of inorganic fertilization were almost negligible as reported elsewhere.

Lack of agreement between models and the 1998 SOC measurements on sorghum might corroborate a general tencency to underestimate initial SOC decline after conversion to cropland (Coleman et al. 1997), notably in tropical soils with accelerated SOM cycles (McDonagh et al. 2001), but could also be due to errors. It is possible that the root : shoot ratio decrease induced by fertilization and noted on grassland by Coleman et al. (1997) could enhance contrast between SOC trends in treatments with residue incorporation and treatments without.

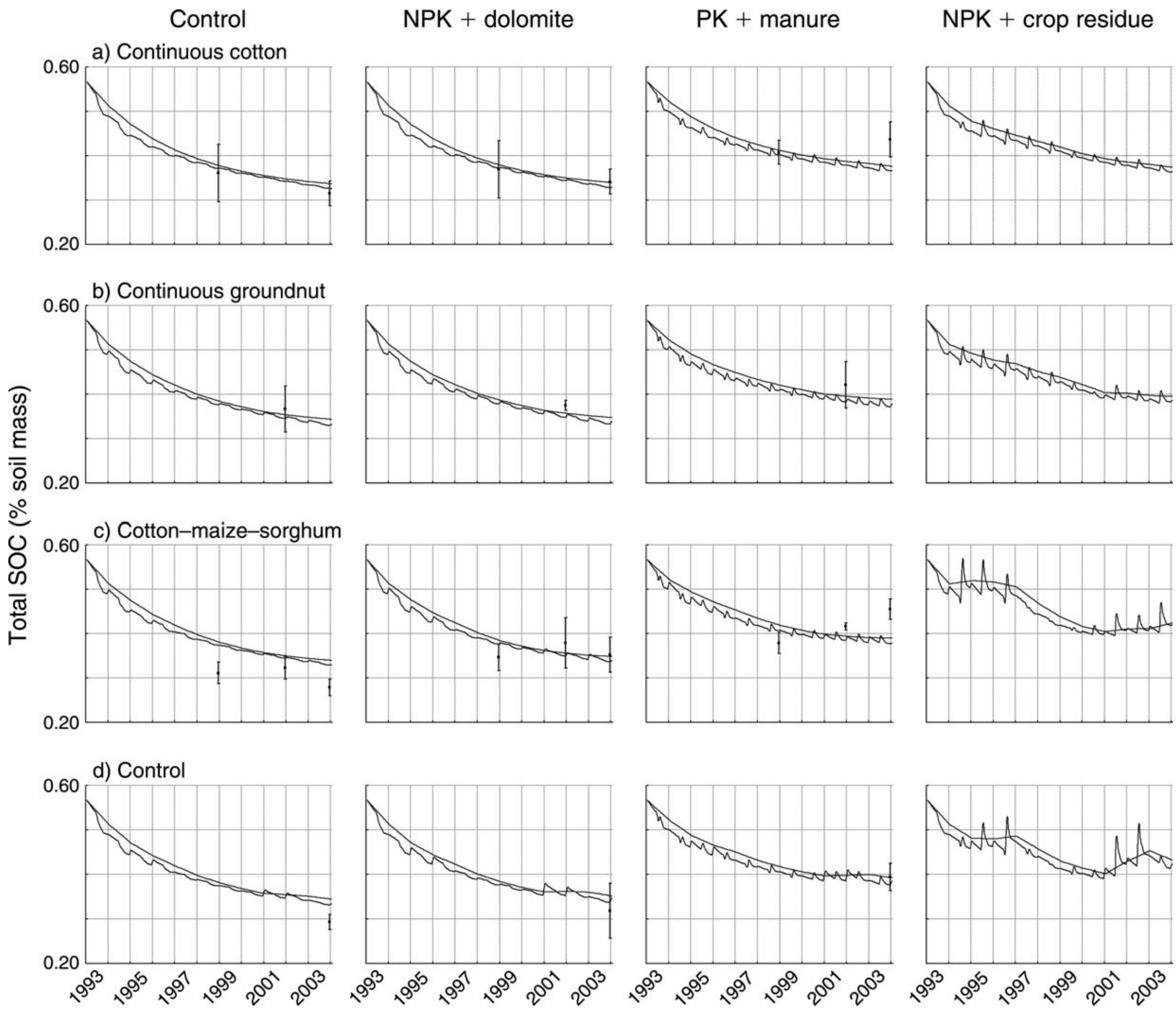

FIG. 5. Simulated C management options for 16 rotations (4 crop treatments [a–d] × 4 fertilizer treatments), showing total SOC content (%) simulated by RothC (relatively smooth curve in each panel) and by a yearly two-pool model (jagged lines). Error bars represent ±SD from measurements mean.

DISCUSSION

Hierarchies of scale in modeling meta-stable and transient dynamics (Wu and Loucks 1995) imply that some timescales (i.e., turnover pools) are more relevant than others depending on the process studied. For agricultural C sequestration, intermediate, decadal time scales are key, emphasizing the significance of passive pools. Yet the definition of "stabilized" organic matter is not experimentally verifiable and changes as a function of research objectives, data-set characteristics and model formalization. For example, the proposed 50-year turnover time for humified organic matter (HUM) is

TABLE 5. Offsets in soil organic carbon (SOC) loss (%) occasioned by various practices compared to the control scenario (11-year duration), as simulated by the two-pool model.

		Treatment						
Crop rotation	Control	PK fertilizer	NPK fertilizer	NPK + dolomite	PK + crop residue	NPK + crop residue	PK + compost	PK + manure
Cotton continuous	−40	−40†	−40	−40	−37†	−35†	−35†	−33
Groundnut continuous	−40	−40†	−40	−36	−32†	−30†	−33†	−32
Sorghum continuous	−42	−42†	−40	−40	−33†	−26†	−35†	−33
Cotton–Maize–Sorghum	−40	−40†	−39	−39	−28†	−25†	−35†	−32
Groundnut–Sorghum–Cotton	−40	−40†	−40	−38	−28†	−26†	−33†	−32

† These predictions correspond to treatments without SOC measurements.

probably not fortuitous given the specific longevity of data sets used for model design and fitting. Subsequent inclusion of older material in an arbitrarily inert device with infinite turnover (inert organic matter [IOM] in the RothC model) could prove adequate for 20-year C-sequestration contracts where a dynamic passive pool (like Century's SOM3) is not required. However, reducing the number of pools involves a redefinition of age classes: the stable fraction (S) in our two-pool model is not equivalent to the sum of HUM + IOM in RothC, which, if DPM + RPM + BIO (decompostable plant material + resistant plant material + microbial biomass) was interpreted as the labile fraction, might convey an unrealistic view of plant-available C (small enough after five years to trigger an inflection in the HUM + IOM curve: Fig. 4). Most two-pool models investigated so far rely on a dynamic slow component, and our study suggests that it can be replaced with an inert compartment without loss of predictive skill. Likewise, pools cycling on irrelevant short frequencies can be simplified through appropriate reduction of the temporal resolution in models: operating RothC on a yearly time step results in a quasi-instantaneous, "transparent" turnover of DPM. This active pool can be eliminated in a simpler yearly model, as it contributes little to total SOC prediction.

Another strong, albeit less discussed incentive for simplification is the limited availability of data, and of information on parameter values and initial conditions, particularly in the Tropics (Diels et al. 2004). Even in simple SOM models, data scarcity aggravates issues of overparameterization and equifinality, raising doubts on the appropriateness of traditional statistical parameter estimation procedures (Schulz et al. 1999); here "overparameterization" refers to the impossibility of identifying one single "best" parameter set, and "equifinality" indicates that equivalent predictions might arise from the use of different parameter sets (Beven 2006). Multiple solutions can yield concordance with observed data (Feng and Li 2001), increasing simulation uncertainty across a range of boundary conditions. This situation occurred in the variability of optimized states and parameters in RothC (results not shown). At equivalent predictive quality levels (below 10 kg C/ha variation in total SOC), relocation of up to 1.5 Mg C/ha were observed between initial HUM and IOM followed by increases in the decay rates k_{HUM} and k_{RPM}, depending on the way the optimization procedure was initialized (starting at a nominal value vs. 0). Similar observations were made when introducing artificial errors in the computation of RothC's moisture rate modifier (b) or the omission of the HUM-to-HUM recycling flux, with a marked tendency to relocate SOM between HUM and IOM or vice versa, or similarly to "transfer" decomposability between k_{RPM} and k_{BIO}. Although this plasticity (Larocque et al. 2006) takes place between relatively comparable components in agreement with results from sensitivity analyses, it becomes irrelevant when using a two-pool model. Good parameter values and good predictions are related but not identical (Makowski et al. 2006), and many parameter values are not required for good SOC predictions.

Uncertain information adds to data scarcity in support of simple models. Oblivious to this work is the assessment of initial conditions, which bears a critical impact on any C-sequestration project. In the controlled conditions of Farako-Ba (Burkina Faso), agricultural disturbance was effectively preceeded by a long-term fallow. On potential farmer-contract areas in the Tropics, the determination of historical land use might prove exceedingly uncertain as farmer recollection decreases over time and agricultural statistics are not reliable enough to be used (e.g., as in Zimmerman et al. [2005]). Baseline certification options for verification agencies could include the historical documentation of cropland expansion using low-cost satellite time series such as Corona, Landsat with change detection, and spatial analogue methods (McDonagh et al. 2001). However, a substantial level of doubt will continue and affect the translation of initial SOC measurements into departures from a steady state, more so for complex models where longer spin-ups (initialization processes by which a model is allowed to reach a steady state [here, steady distribution of SOM across model pools])—or arbitrary decisions—might be required to allocate SOM among numerous pools. Fitted against SOC measurements and driven by biomass measurements, RothC and the two-pool model can only predict total SOC within $\sim$1.5 Mg C/ha (RMSE) of its actual value. This error will increase when predictions are made with uncertain initial conditions, parameters, and driving variables. Methods to further quantify and reduce uncertainty in operational verification frameworks include stochastic models, data assimilation, geostatistics, and remote sensing (Bostick et al. 2003, Zimmerman et al. 2005, Liu et al. 2006, Jones et al. 2007, Mooney et al. 2007).

Conclusion

There are multiple uncertainties in our understanding of SOC dynamics at various heuristic levels: uncertain data (from diverse collection protocols and analysis standards), uncertain information (e.g., relative to steady or transient states), and uncertain knowledge (formalized along unverifiable concepts). The "modeling the measurable or measuring the modelable" paradigm (Motavalli et al. 1994) hints at the large level of uncertainty affecting both measurements and models, and at constraints occasioned by data paucity.

The nested, hierarchical nature of SOM turnover (Christensen 2001) can be discretized into custom compartments, the individual importance of which depends on the process studied and its relevant timescales. For putative 20-year C-sequestration contracts, interannual to interdecadal dynamics are key. Faster (seasonal) and slower (semicentennial and beyond) rates can be approximated by constants as instantaneous and infinite decay, representing the asymptotes of the "hockey-stick" exponential decay function (Feng and Li 2001).

A discrete, yearly, two-pool SOC model composed of one stable (nearly inert on contractual timescales) and one labile compartment successfully predicted C decomposition in a controlled long-term fertilization trial in subhumid Burkina Faso. In hindcast mode and after parameter estimation, it performed equally well as RothC version 26.3 for total SOC simulation (+0.2% difference in RMSE), and exhibited comparable predictive skill on independent treatments, including those with residue incorporation. RothC sensitivity analysis (Janik et al. 2002) and exploratory optimization provided a heuristic base for this reduction approach. At comparable predictive levels, a simpler structure should mitigate risks of equifinality and resulting simulation uncertainties.

With the benefits of simplification, including a better understanding of the system and various derived applications including upscaling (Brooks and Tobias 1996), the two-pool model features an adequate level of complexity for spatial integration over patchy contract areas on relevant time spans. In fact, if statistical appraisal cannot positively identify outstanding performance across a set of models (e.g., Smith et al. 1997), then other evaluation criteria, including simplicity, should be considered. Unavoidable residual errors arising from model structure, limited baseline information, and data quality and quantity will be handled more efficiently in a light, stochastic data assimilation framework involving the use of remote sensing and complementary in situ measurements.

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