

Modelling long-term impacts of novel biobased fertilizers on soil C storage from laboratory short-term mineralization

E. Ronchin*, T. Sinicco and C. Mondini
CREA Research Centre for Viticulture and Enology, Gorizia, Italy
*erika.ronchin@crea.gov.it

INTRODUCTION

The growing emphasis on circular food economies and sustainable agriculture is driving the recycling of exogenous organic matter (EOM) through the production of **biobased fertilizers (BBF)**. While this provides an opportunity to reduce reliance on mineral and synthetic fertilizers, uncertainty exists regarding the **long term impact of BBF application** on soil organic matter dynamics. This study aims to model the impact of novel BBFs — such as microbial biomass, insect biomass, insect frass, biochar, and derived blends, produced in the framework of H2020 project RUSTICA — on long term soil C storage. For this purpose, we used a **modified version of the RothC model** encompassing additional EOM pools. We calibrated EOM pools' parameters, specifically pools' size and decay rates, through inverse modelling of BBF and derived blend mineralization rates measured with a gas chromatography system (Fig. 1) from amended soil.



Figure 1. Automated gas chromatography system for GHG analyses of amended soils incubated in laboratory.

METHOD 2: INVERSION of GC signals provides the KINETIC PARAMETERS FOR EACH BIO-BASED FERTILIZER and BLEND



- Inverse modelling of mineralization rates is based on a modified Rothamsted carbon model (ROTHC) (Coleman and Jenkinson, 1996) to deconvolute the CO₂ efflux of amendments into EOM C-pools specific decay rates and size.
- A new R function of modified ROTHC, according to Mondini et al. (2017), foresees three additional EOM C pools (decomposable (DEOM), resistant (REOM), and humified (HEOM)), with specific partition coefficients. It is also possible to assign specific decomposition rates to DEOM and REOM, while HEOM has a fixed decomposition rate of 0.02 y⁻¹.
- The simulations of soil respiration are run under the same incubation conditions.
- For the estimation of optimal kinetic parameters of BBF and blends, we perform an inversion of the measured mineralization rates of the incubations (Fig. 3) with a Bayesian approach using the Differential Adaptive Metropolis (DREAM) algorithm (Scharnagl et al. 2010 and references therein, Joseph and Guillaume, 2011 and 2013). This allows us to infer the probability density functions of the values for C-pools size and their C-pool-specific decay rates (Fig. 4).

- Working with novel BBF, little is known about their kinetic parameters. Therefore, constraining the search of parameter estimates within a predefined space of solutions is a way to guide the search without starting from a specific (unknown) value. The search space for each parameter is defined by bounds taken from literature of similar products (from Woolf et al. (2023) for the biochar, and from Mondini et al. (2017) for the other BBF) and expanded to broaden the search and reach a more robust solution, when necessary.

- The RothC condition that forces the sum of all EOM pools to 1, allows to describe the size of the resistant pool (f.REOM) and humified organic matter pool (f.HEOM) in function of the size of a repartition factor between them (rep.f.REOM.HEOM) and the size of the decomposable pool (f.DEOM):

$$f.REOM = (1 - f.DEOM) * rep.f.REOM.HEOM$$

$$f.HEOM = (1 - f.DEOM) * (1 - rep.f.REOM.HEOM)$$

- This reduces the search of optimal values to 4 parameters (DEOM pool size, the repartition factor, and the C-pool-specific decay rates k.DEOM and k.REOM)

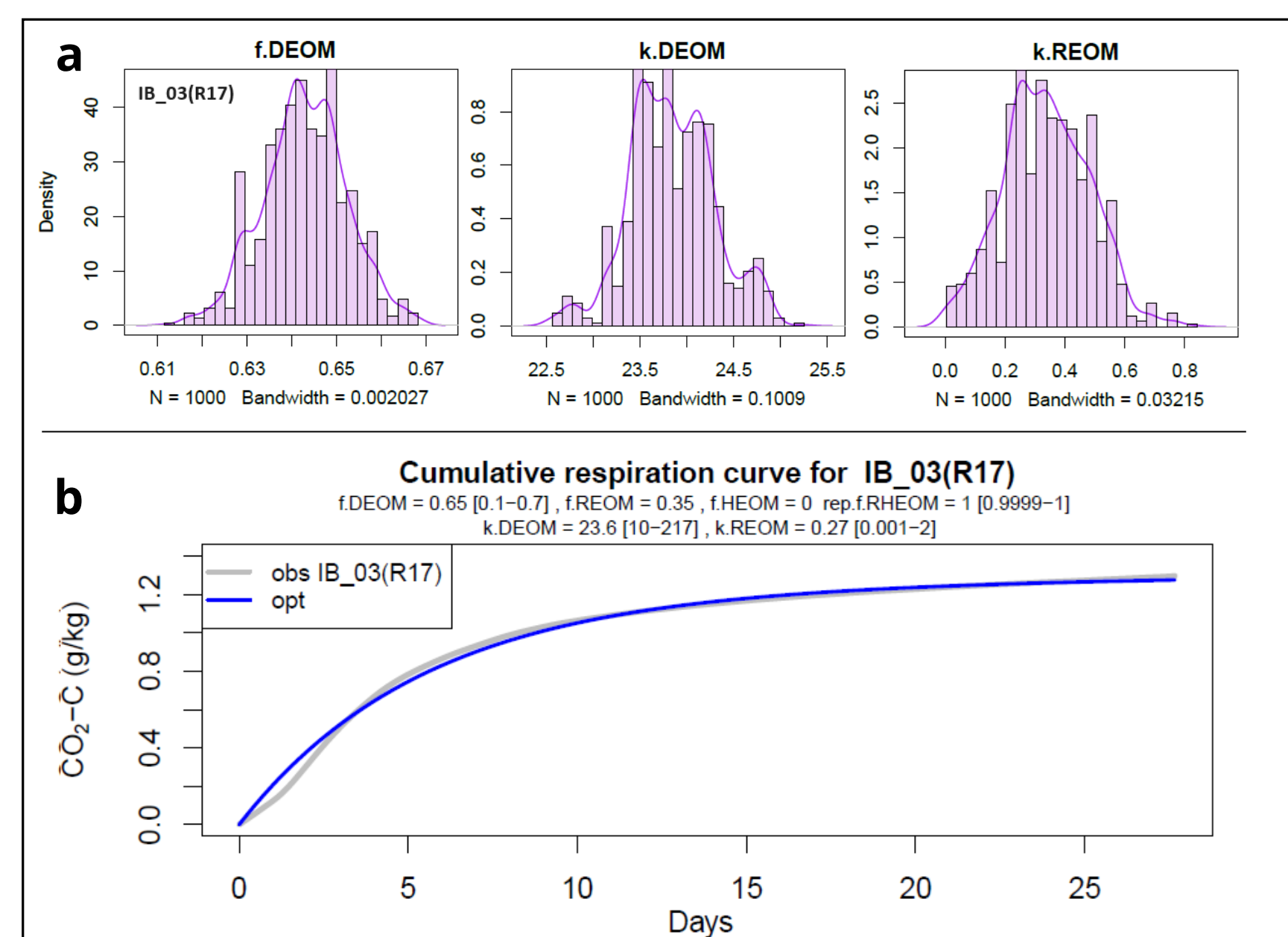


Figure 4. Example of simultaneous estimation of kinetic parameters and respiration fitting. (a) marginal posterior probability distributions of 3 EOM pools of ROTHC. Histograms are constructed using a subset of the 50% most represented sample values generated with DREAM after convergence, (b) fit of the respiration curve.

DISCUSSION AND CONCLUSIONS

Single-component BBF
Single initial addition results show the stability of each BBF. Biochar stands out with 96.6% C remaining after 100 years, indicating its stability and effectiveness in soil C sequestration. Compost, insect biomass, insect frass and microbial biomass (18.2, 4.3, 5.0 and 4.7 %, respectively) degrade faster. Continuous annual amendment simulations reveal biochar significantly increases SOC stocks by 119%, while compost contributes 52%. Other BBF contribute less to long-term sequestration, with annual rate of C sequestration around 0.13 ton C/ha/y, but offer other soil benefits.

Blends of BBF
Blends with biochar show varied C retention (13.1% to 82%) after 100 years, depending on biochar content (0% to 60%). Biochar stabilizes more degradable materials in blends, such as insect and microbial biomass, impacting SOC accrual. Blend FVG4 (41% biochar) and FVG3 and PdL3 (69 and 60% biochar, respectively) show similar values of remaining C (Fig. 9). For continuous amendment, SOC stocks increase by 36% to 108% over 100 years, correlating with biochar content (r = 0.91; p < 0.05). The blends show a significant C sequestration potential with annual rate in the range 0.30-0.89 ton C/ha/y.

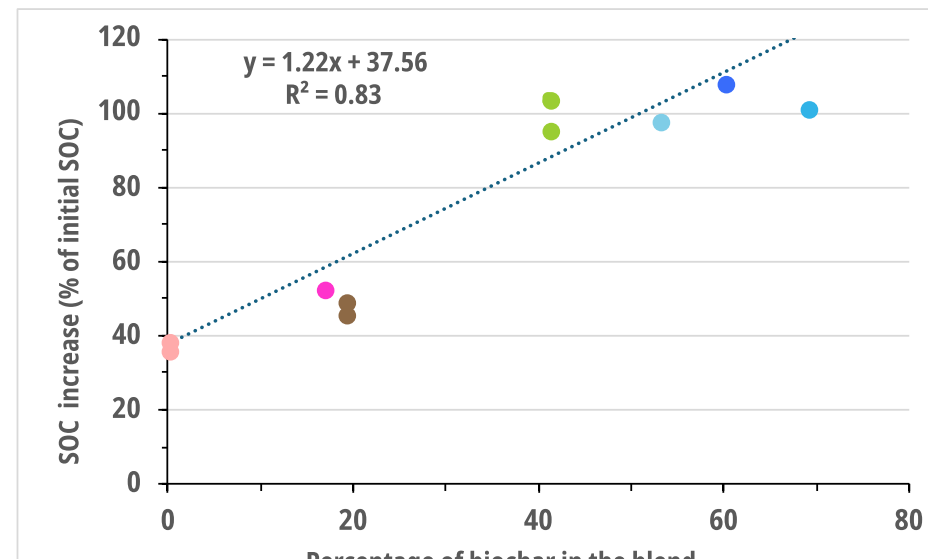


Figure 9. SOC increase as a function of the percentage of biochar in the blend (colors as in Fig. 8).

METHOD 1: Incubation and respiration signals of blends

- Mineralization rates of 50 g (over-dried bases) preconditioned soil, amended with a dose of 0.5% (w.w) of diverse BBF (Fig. 2) and derived blends, were recorded during a 30 days aerobic incubation under controlled conditions of humidity (about 40% of soil water holding capacity) and temperature (20°C). Among the amendments we also included compost, as it was utilized in the formulation of the blends.

- Samples were incubated in sealed plastic jars (Fig. 1) continuously aerated at a constant flow rate (15 ml min⁻¹) for determination of CO₂ evolution every 4 h (in triplicate) with a continuous gas sampling and analysis system.

- Mineralization rates of amendments (Fig. 3) were isolated from the contribution of the soil CO₂ efflux by subtracting the efflux of a control (untreated soil).

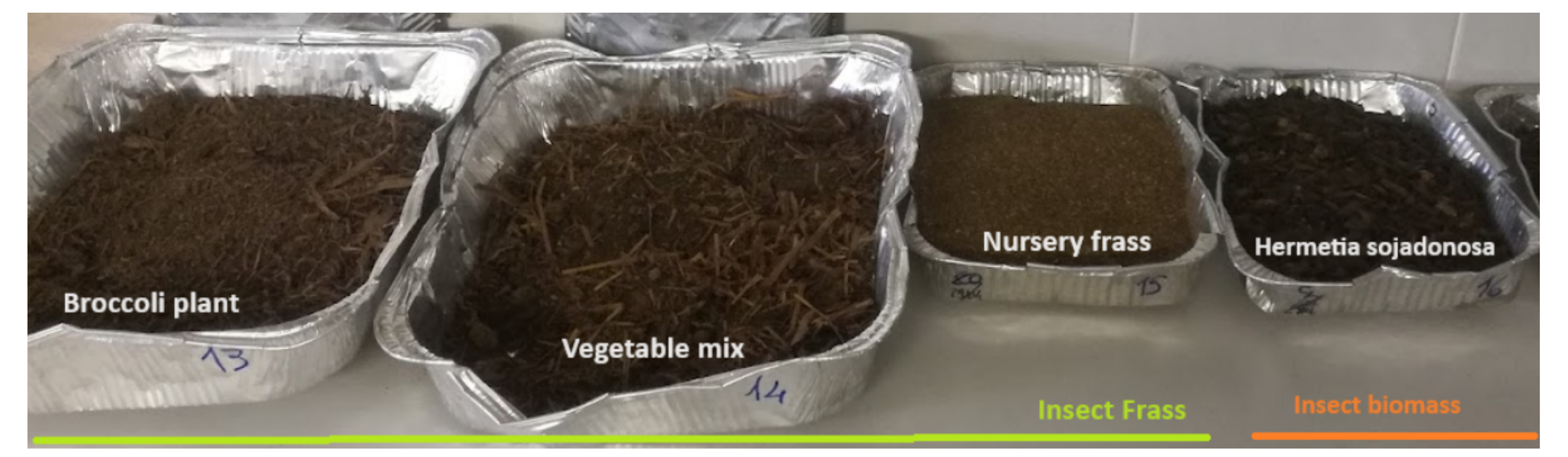


Figure 2. Some of the BBF used for the laboratory experiments before drying, grinding, and sieving at 1 mm.

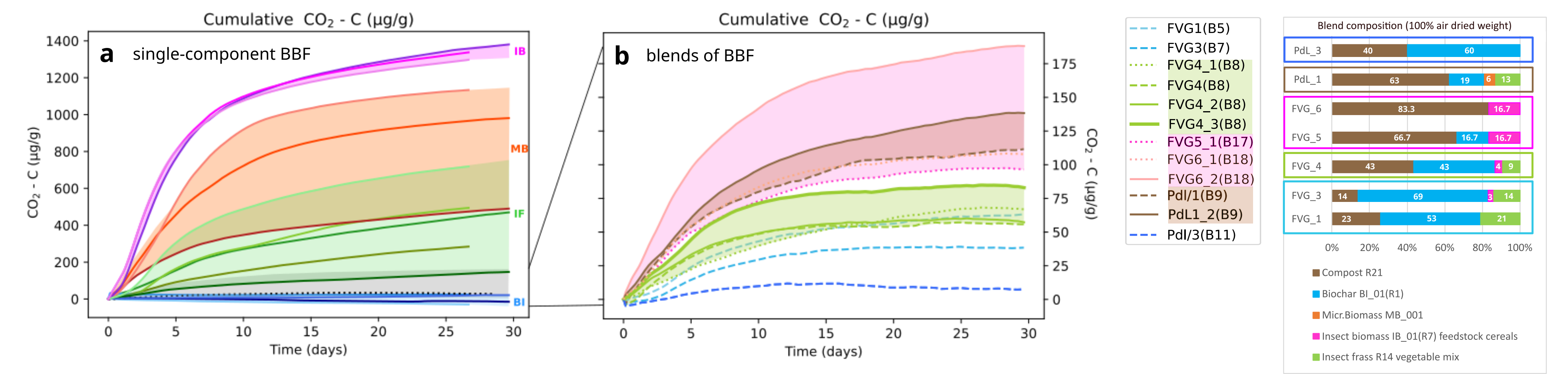


Figure 3. CO₂ emissions. Cumulative respiration curves during the 30-day incubation. Each curve is the result of outliers removal and averaging of three signals from three replicates for: (a) single-component BBF and (b) blends of BBFs. Colors as in Fig. 7 and Fig. 9, respectively.

RESULTS: calibration of kinetic parameters and long-term predictions of SOC in soil amended with BBF and BBF blends

Calibration of kinetic parameters

group	type	BBF	C added (µg/g)	f.DEOM	f.REOM	f.HEOM	k.DEOM	k.REOM	feedstock
BI	biochar	BI_02(R2)	2278	0.02	0.98	0	5	0.0002	willow wood and peppers
comp	compost	Comp(R21)	1055	0.03	0.25	0.71	25	0.10	urban compost
IB	insect larvae biomass	IB_01(R7)	2832	0.59	0.41	0	19	0.03	cereals
IB	insect larvae biomass	IB_02(R16)	2345	0.67	0.33	0	23	0.31	cereals
IB	insect larvae biomass	IB_03(R17)	2367	0.65	0.35	0	24	0.26	cereals
IF	hermetia insect frass	IF_02(R5)	2235	0.18	0.82	0	12	0.44	Bear bagasse
IF	hermetia insect frass	IF_04(R13)	1369	0.27	0.73	0	7	0.24	Broccoli plant
IF	hermetia insect frass	IF_05(R14)	1488	0.29	0.71	0	12	0.97	Vegetables mix
IF	hermetia insect frass	IF_06(R15)	1972	0.48	0.52	0	12	0.02	cereal
MB	microbial biomass	MB_1.5(R9)	1208	0.33	0.67	0	27.54	1.211	Paprika
MB	microbial biomass	MB_4.1(R10)	2129	0.64	0.36	0	16.18	0.022	market waste
MB	microbial biomass	MB_4.2(R18)	2211	0.67	0.33	0	15.83	0.087	market waste: carrots

blend composition	BBF	C added (µg/g)	f.DEOM	f.REOM	f.HEOM	k.DEOM	k.REOM
23% comp (R21), 53% BI(R1), 21% IF(R14)	FVG1(B5)	1125	0.07	0.70	0.22	12.85	0.0007
14% comp (R21), 69% BI(R1), 3% IB_01(R7), 14% IF(R14)	FVG3(B7)	1403	0.04	0.74	0.22	15.30	0.0010
43% comp (R21), 43% BI(R1), 4% IB_01(R7), 9% IF(R14)	FVG4_1(B8)	756	0.13	0.70	0.17	8.66	0.0005
	FVG4(B8)	1375	0.05	0.76	0.18	23.20	0.0005
	FVG4_2(B8)	1512	0.05	0.77	0.18	20.98	0.0006
	FVG4_3(B8)	2268	0.05	0.77	0.19	20.22	0.0007
66.7% comp (R21), 16.7% BI(R1), 16.7% IF_01(R7)	FVG5_1(B17)	687	0.17	0.56	0.26	16.42	0.0220
	FVG6_1(B18)	573	0.20	0.27	0.53	19.84	0.5633
83.3% comp (R21), 16.7% BI(R1)	FVG6_2(B18)	1145	0.17	0.35	0.48	20.61	0.3978
63% comp (R21), 19% BI(R1), 6% MB, 13% IF(R14)	PdL1(B9)	1218	0.11	0.29	0.60	18.46	0.0978
	PdL1_2(B9)	1173	0.14	0.61	0.25	14.17	0.0285
40% comp (R21), 60% BI(R1)	PdL3(B11)	1915	0.01	0.80	0.19	33.86	0.0005

Figure 5. Tables with the information of the BBF composition and estimates for EOM C-pools size and C-pool-specific decay rates from DREAM for (a) single-component BBFs and (b) blends of BBF. In brackets are the upper and lower bounds that define the search space for each parameter. Ternary plots: distribution of BBF groups based on their optimized C-pool size.

Long-term predictions of SOC in soils amended with BBF and BBF blends

Before running the long-term simulation of C storage in soil amended with different BBF and blend, we used the spin-up phase (Fig. 6) of the RothC model to compute the size of soil organic C pools at the equilibrium for a specific vineyard soil (Corno di Rosazzo, Italy). We used monthly averaged climate data (temperature, precipitation, and PET) of 30 years (1990-2010) and information about land management and soil coverage to take into account the conditions of typical vineyard in NE Italy. We hypothesized two long-term (100 years) scenarios of soil amendment: (a) single initial addition of 10 ton C/ha (Fig. 7a and Fig. 8a) and (b) annual addition at a rate of 1 ton C/ha/y (Fig. 7b and Fig. 8b).

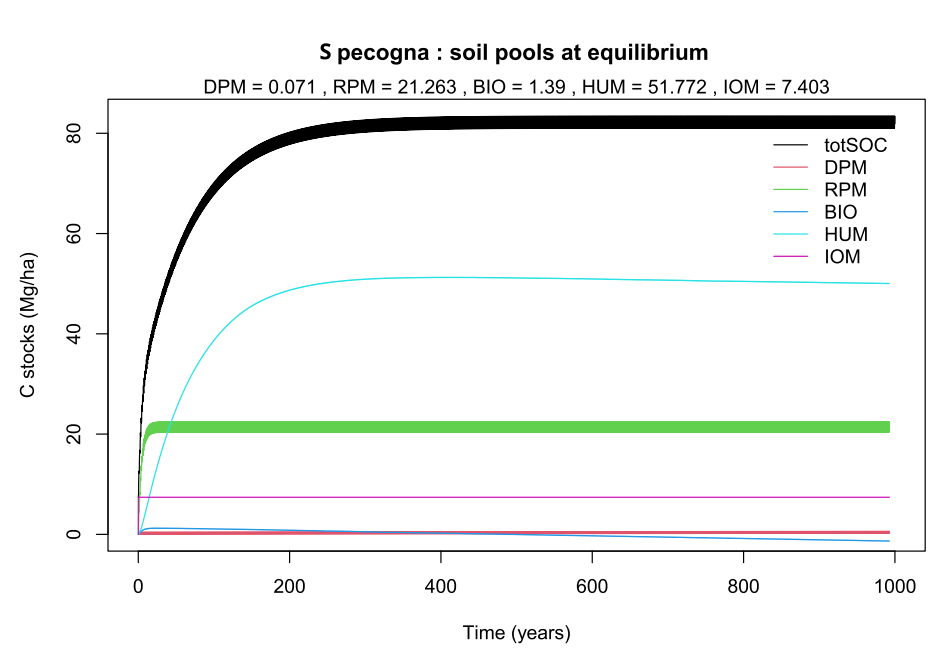


Figure 6. Soil C pools size at equilibrium: DPM = 0.071, RPM = 21.263, BIO = 1.39, HUM = 51.772, IOM = 7.403.

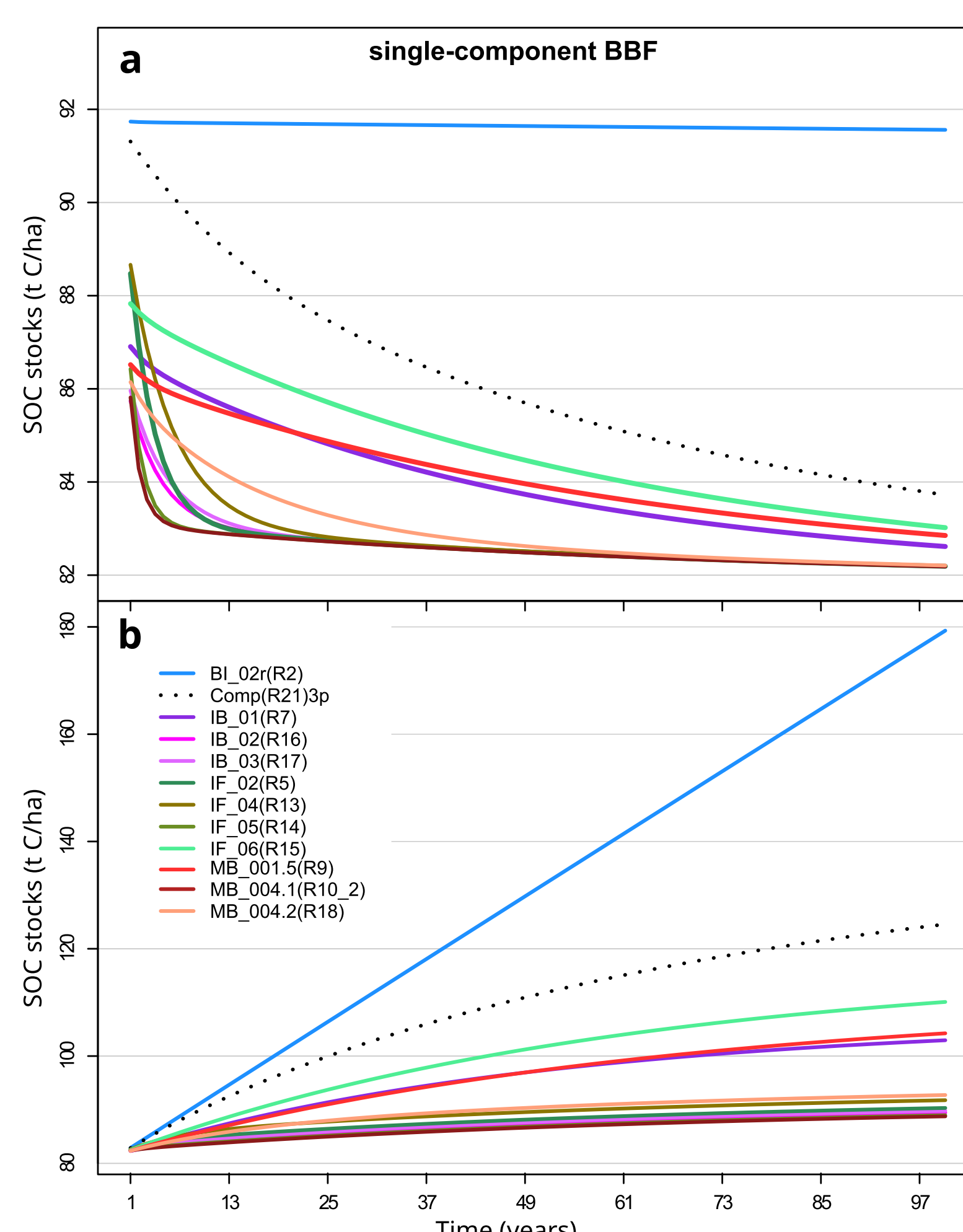


Figure 7. Long-term prediction of SOC for the single-component BBF. (a) Single initial addition of 10 ton C/ha, and (b) Annual addition at a rate of 1 ton C/ha/y.

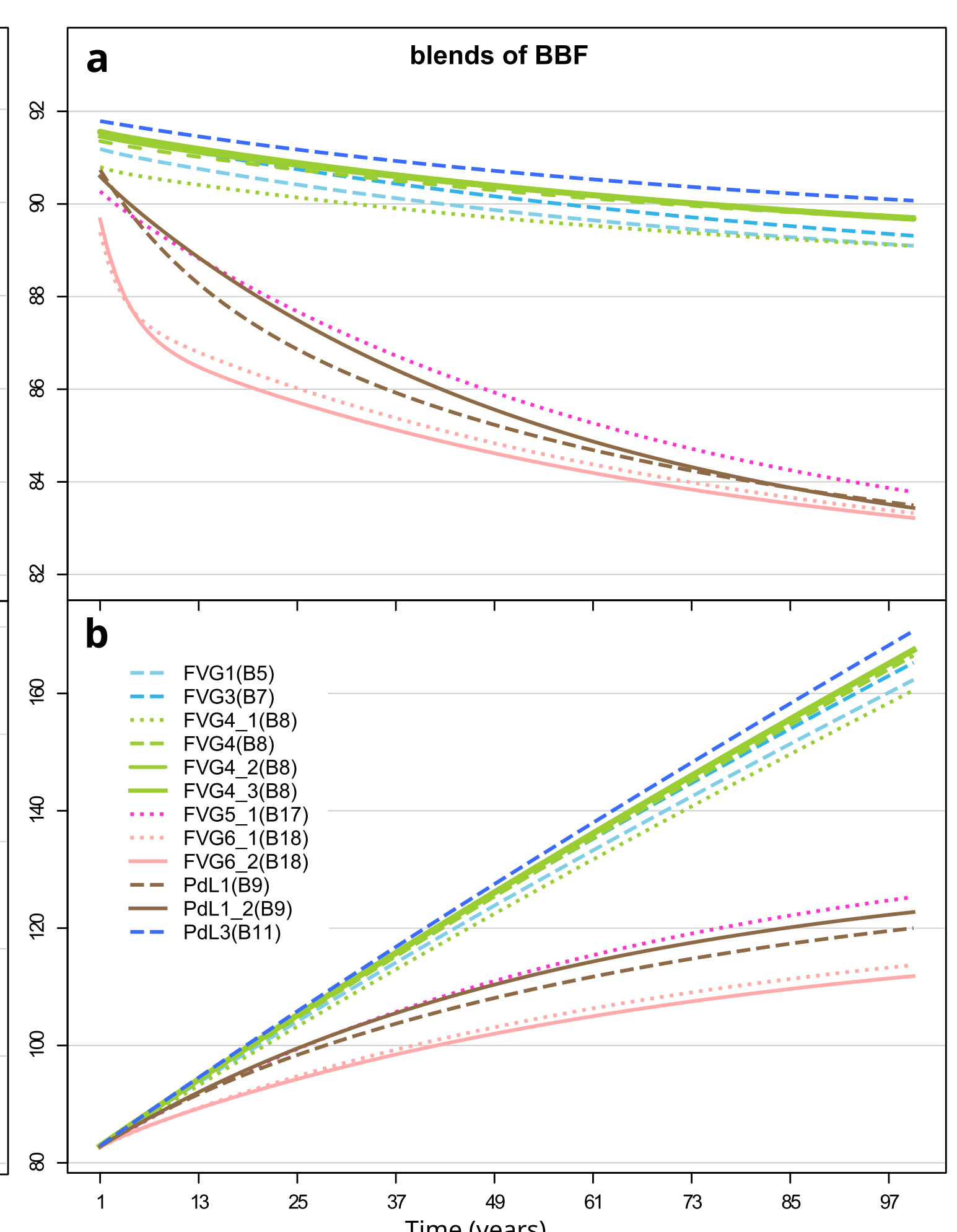


Figure 8. Long-term prediction of SOC for blends of BBF. (a) Single initial addition of 10 ton C/ha, and (b) Annual addition at a rate of 1 ton C/ha/y.

Bibliography

- Coleman, K., Jenkinson, D.S., 1996. RothC-26.3 - A Model for the turnover of carbon in soil, in: Powlson, D.S., Smith, P., Smith, J.U. (Eds.), Evaluation of Soil Organic Matter Models. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 237-246.
- Mondini, C., Cayuela, M.L., Sinicco, T., Fornasier, F., Galvez, A., Sánchez-Monedero, M.A., 2017. Modification of the RothC model to simulate soil C mineralization of exogenous organic matter. Biogeosciences 14, 3253-3274. [https://doi.org/10.5194/bg-14-3253-2017]
- Joseph, J.F., Guillaume, J.H.A., 2013. Using a parallelized MCMC algorithm in R to identify appropriate likelihood functions for SWAT. Environmental Modelling & Software 46, 292-298. [https://doi.org/10.1016/j.envsoft.2013.03.012]
- Scharnagl, B., Vrugt, J.A., Vereecken, H., Herbst, M., 2010. Information content of incubation experiments for inverse estimation of pools in the Rothamsted carbon model: a Bayesian perspective. Biogeosciences 7, 763-776. [https://doi.org/10.5194/bg-7-763-2010]
- Sierra, C.A., Müller, M., Trumbore, S.E., 2014. Modeling radiocarbon dynamics in soils: SoilR version 1.1. Geoscientific Model Development 7, 1919-1931. [https://doi.org/10.5194/gmd-7-1919-2014]

Acknowledgements and media spaces

THIS PROJECT HAS RECEIVED FUNDING FROM THE EUROPEAN UNION'S HORIZON 2020 RESEARCH AND INNOVATION PROGRAMME UNDER GRANT AGREEMENT NO 101000527

