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Full Length Research Paper

Soil carbon dynamics, climate, crops and soil type – calculations using introductory carbon balance model (ICBM) and agricultural field trial data from sub-Saharan Africa

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A simple soil carbon model, the Introductory Carbon Balance Model (ICBM), is useful for projecting soil C dynamics in temperate and tropical land-use systems. A spreadsheet-based version of ICBM is presented, with an emphasis on African and short-and long term projections under variable conditions (climate, crops, soil). ICBM has two compartments, young and old soil C, and five parameters, intended to project soil C dynamics in a 30-year perspective even when detailed data are lacking. Information necessary is a rough estimate of annual carbon input to soil, a coarse measure of residue quality and some information about climate. If basic weather station data and water-related soil properties are available, more exact projections can be made. Typically, the model is used for answering questions such as: (1) If crop residues are returned to the field, how much will soil carbon increase after 30 years? (2) With limited local data available, will rough estimates (climate zone and crop yield etc) still make projections possible? Compared with more complex models, this approach is rapid and simple and yet still gives accurate results. The model is available as an Excel® spreadsheet, and which projections can be made and effects of different agricultural treatments can be compared. Here, agricultural field experiments in Africa are used to show how ICBM rapidly can be parameterized for conditions different from those it was originally calibrated for, and how projections can be made from this base parameterization. Concepts behind modeling approaches, as well as possible improvements, are also discussed.

Key words: Soil carbon, agriculture, modeling, carbon sequestration, Africa.

INTRODUCTION

This paper presents a spreadsheet-based version of Introductory Carbon Balance Model (ICBM) in order to aid soil scientists and managers of long-term experiments, with an emphasis on African conditions, with short-and long term projections under variable conditions (climate, cropping system and soil types).

Modeling of soil C dynamics has received a lot of attention during the last decades. Soil carbon and its dynamics has been recognized for a long time as a crucial soil component for example, (Tenney and Waksman, 1929; Henin and Dupuis, 1945), but with the recognition of soils as sources/sinks for the greenhouse gas CO_2, there has been a major surge in the development of soil carbon modeling. For example, GEFSOC, a generally applicable coupled GIS/modeling system using the well known models RothC (Coleman and Jenkinson, 1996) and Century (Parton et al., 1987), as well as IPCC. Tier 1 calculations have recently been presented (Milne et al., 2007). The Introductory Carbon Balance Model (ICBM) (Andrén and Kätterer, 1997) was devised as an intermediate between IPCC Tier 1 linear calculations (IPCC, 2004) and there are more complex modeling approaches (Grace et al., 2006). A variety of models have been used to simulate soil carbon dynamics within African agricultural field experiments, including RothC (Diels et al., 2004; Farage et al., 2007b; Kamoni et al., 2007) and Century (Woomer, 1993; Tschakert et al., 2004; Farage et al., 2007a; Kamoni et al., 2007), but Agricultural Production Systems Simulator (APSIM) (Micheni et al., 2004) and other models have also been applied. The complexity of these models are related to the number of storage pools used to simulate soil carbon dynamics, and naturally also to how many and how complex drivers are included in the model (for example, climate drivers and plant growth sub-models). The simplest models suitable for simulating long-term dynamics over some periods of decades, utilize a single dynamic pool plus an additional, inert, pool that resides outside of the model dynamics (McNair et al., 2007).

On the other hand, the more complex models utilize between four (RothC) and six (Century) more or less dynamic soil carbon pools and have adequate complexity to at least attempt to model short-term dynamics (on the order of weeks and months) as well.

ICBM was originally conceptualized with one rapid and one slow soil carbon pool (Andrén and Kätterer, 1997), which is the minimum required to capture aspects of both short and long-term dynamics. If required, a third inert carbon pool can be readily added to ICBM to represent an inert partition of the total soil carbon mass. In terms of model functionality, this partition then remains static outside the dynamics of the two active pools.

Well-documented models such as RothC, Century and APSIM provide pre-defined default or “standard” parameter values, primarily identified from calibrations to long-term field trials in the regions where these models were developed (England for RothC, Great Plains, U.S.A. for Century, and Australia for APSIM). These models have all been subsequently tested in numerous climate zones throughout the world, and it is generally assumed that these standard parameter sets are robustly portable. However, in a recent study using African data, standard decomposition rates in the RothC model had to be doubled to model a long-term dataset from Ibadan, Nigeria (Diels et al., 2004). As with the aforementioned models, ICBM was originally parameterized to a long-term field trial, in this case in Uppsala, Sweden (Andrén and Kätterer, 1997). Recently, a climate- and soil-based activity index was presented for ICBM, which in theory, provides for model portability by estimating a site-specific soil activity index relative to the Uppsala site (Andrén et al., 2007). Long-term soil carbon trends found in African field trial datasets can be characterized as typically either gently upward sloping, asymptotically downward sloping, or in steady state, depending upon treatments and local conditions, with inter-annual variations scattered around these overall long-term trends (Diels et al., 2004; Kamoni et al., 2007; McNair et al., 2007). This data scattered within the long-term trends is due to an inseparable combination of actual inter-annual variation (for example, large differences in carbon inputs between years) and inherent stochastic uncertainties in soil carbon mass quantification (Karlsson et al., 2003; Bricklemyer et al., 2005; Ogle et al., 2007). Typically, the inter-annual dynamics seen in African datasets have proven difficult to simulate, even with some of the more complicated soil carbon models. For instance, in a study that applied RothC and Century models to long-term datasets from Kabete and Machang’a in Kenya, long-term trends were generally well simulated by both models in most treatments, but inter-annual variations were absent from the simulations (Kamoni et al., 2007).ICBM was originally conceptualized as a model of minimal complexity with capabilities for reproducing both short- and long-term dynamics. The relative simplicity of the ICBM model structure seems to match both the gentle long-term dynamics and inherent uncertainties that typify data in most long-term African (and also most data sets from temperate climates) field trials. In this paper, a spreadsheet-based version of ICBM is presented and intended to assist soil scientists and managers of long-term experiments, with emphasis on African conditions interested in soil C projections using limited climate, cropping systems and soil type data. This tool is aimed towards non-modelers, with the intent of providing a rapid means of producing estimates of impacts from various future management scenarios or to assess the sensitivity of existing long-term data in response to various experimental treatments. To demonstrate the suitability of ICBM for this purpose, we use data from the same long-term field trial at Machang’a, Kenya that has been used for modeling with RothC and Century (Kamoni et al., 2007), as well as APSIM (Micheni et al., 2004). This provided a common basis for comparing modeling results and ease of use to these other approaches.

MATERIALS AND METHODS

Introductory carbon balance model (ICBM)

The Introductory Carbon Balance Model (ICBM), has two state

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Table 1. The parameters of the ICBM model, typical dimensions and typical range of values used.

Parameter	Symbol	Typical dimension	Typical range
Input	***i***	**t ha^{-1} year^{-1}**	**0-5**
Decomposition rate constant for *Y*	k_Y	Year^{-1}	0.8
Humification factor	h	Dimensionless	0.1-0.6
Decomposition rate constant for *O*	k_O	Year^{-1}	0.006
External control factor	r_e	Dimensionless	0.8-5

Input also commonly is expressed as kg m^{-2} year^{-1} and k_Y and k_O often, but not always, are unchanged from the original calibration.

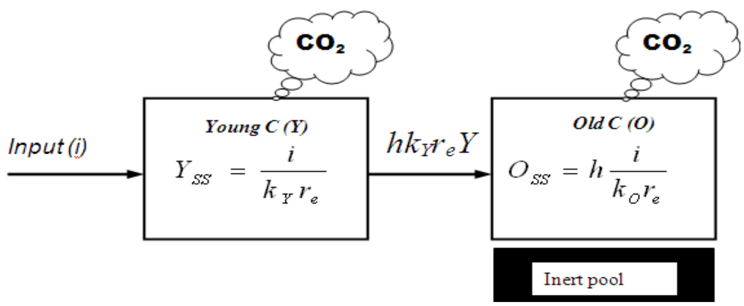

Figure 1. The ICBM model. *i* = (annual) input, *Young C (Y)* = young soil carbon, *Old C* (O) = old soil carbon, k_Y = fraction of *Y* that decomposes (per year), k_O = fraction of *O* that decomposes (per year), *h* = humification coefficient, r_e = external influence coefficient. The index "SS" denotes the equation for calculating the steady-state value for that pool. Complete list of equations as well as strategies for estimating parameter values is given in Andrén and Kätterer (1997)

variables or pools, "Young" (*Y*) and "Old" (*O*) soil carbon. ICBM has five parameters: *i*, k_Y, *h*, k_O, and r_e (Table 1 and Figure 1). The "humification coefficient" (*h*) controls the fraction of *Y* that enters *O* and (*1-h*) then represents the fraction of the outflow from *Y* that becomes CO_2–C.

Parameter r_e summarizes all external influence (mainly climate) on the decomposition rates of *Y* and *O*. Note that r_e only affects decomposition rates; r_e does not influence *i* or *h* (Figure 1) (Andrén and Kätterer, 1997) for complete list of equations as well as strategies for estimating parameter values.

The model was originally calibrated using data from a Swedish long-term agricultural field experiment with various amendments (manure, cereal straw and sewage sludge, etc) but also a black fallow kept since 1956 (Kirchmann et al., 2004).

The model has been successfully applied to agricultural field data from Sweden (Karlsson et al., 2003), European field trials, Western and Eastern Canadian agricultural regions (Bolinder et al., 2006, 2007a, 2008; Campbell et al., 2007) and Norwegian arable land (Kynding et al., 2012) has been adapted to sub-Saharan African conditions (Andrén et al., 2007). ICBM has also been expanded to a larger family of related model structures, including more carbon pools and also nitrogen dynamics.

The basic idea behind ICBM is to use an analytically solved, five-parameter two-component model for interactive calculations of soil C balances in a 30-years perspective using a spreadsheet program. The reasons for this simple approach are:

1. Easy and rapid to use and understand with usually only three parameters to 'play' with using guessed or 'rule-of-thumb' parameter values. All parameter values used can be reported in a small table, such that the readers can make their own judgments of their validity and can easily repeat or modify the exact model simulations presented.
2. In the majority of cases, observed soil carbon dynamics in a 30-years perspective as well as the precision of soil carbon mass measurements do not warrant a more complex model
3. In spite of the model simplicity, complex and exact data sets and functions can be used to generate the parameter values used in the spreadsheet (Andrén et al., 2007).
4. The simple core model can easily be inserted into more complex applications and run simultaneously as a simulation model for different climates, cropping systems and soils, with many different parameter settings, for example, for national soil C budgets (Andrén et al., 2008) or within a GIS grid.

Making soil C projections

ICBM can be used through an Excel® spreadsheet (www.oandren.com/ICBM). The workbook has four or more input pages, and the user can input a unique set of parameters in each page (Table 2).

For each parameter set, a 30-year projection is instantaneously made, and the results from using the different parameter combinations are presented in separate and combined graphs.

Parameter values and initial carbon mass

A comprehensive description of the initial parameterization of ICBM

Table 2. Excerpt from one page of the ICBM spreadsheet.

i	k_y	k_o	h	r_e	Tot C_0	Y_0	O_0
1.213	0.800	0.006	0.120	1.800	14.820	0.820	14.000
Yss	***Oss***	**Tss**				**Y**	**O**
0.842152	13.50	14.34		**Residence times**		1.250	166.667
Calculate C mass after any time change underlined below					**Percentage/year**	55.067	0.59820
Time, *t*	**Young, *Y***	**Old, *O***	**Total *C***		**Half-lives**	0.866	115.525
50	0.84	13.7885	14.63				

The underlined values for i (t ha^{-1} year^{-1}) , k_Y, $k_{O,}$ h, r_e, as well as the initial C mass divided into Y_0 and O_0 (t ha^{-1} in topsoil) are set by the user. Time, t is also set by the user and used to calculate soil C mass after the chosen number of years. In this example default values are used for h, k_Y and $k_{O,}$.

is given by Andrén and Kätterer (1997), and subsequently, we will suggest how to adapt the parameters to local conditions. First, parameter r_e, which summarizes the external influences on soil organic matter decomposition rates will be discussed. This parameter is mainly based on soil temperature and moisture, but it can also be modified according to different degrees of cultivation or oxygen starvation due to water-logging. Soil temperature and moisture can be calculated from daily meteorological data paired with soil and crop properties, and the daily activity can be calculated using a factor $r_{e\_temperature} \times r_{e\_moisture}$. This approach is common in climate-dependent modeling and is a simple way of describing the fact that when one of the factors is close to zero, the value of the other factor does not matter much – for example, if the soil is very dry, almost no decomposition will take place even if the temperature is +35°C. The daily calculations of activity can be expressed as an annual mean, which in one value combines temperature and moisture conditions and their daily interaction. The degree of soil cultivation (or the difference between cereals and a grass ley) can then be applied as another multiplier, r_{e_cult}. The actual calculations of r_e that are used when climatic (daily temperature, rainfall and evapo-transporation), soil (wilting point, field capacity) and crop (green leaf area, degree of cultivation) data are available are made using a SAS program (SAS Institute, 2003) called *W2r*$_e$, but can also be calculated within a spreadsheet. When the soil properties used for calculation of water storage parameters (water content at wilting point and field capacity) are unknown, these can be calculated from soil texture data (Kätterer et al., 2006).

There is also a simplified climate parameter, r_{e_clim}, which uses a standard soil (clay loam) and cropping system (black fallow) to give a pure climatic factor for comparisons. The value for r_{e_clim} is calculated from standard meteorological data only (daily temperature, rainfall and evapo-transporation), normalized to 1 for Central Swedish climate, and typical values have been calculated for sub-Saharan Africa (Andrén et al., 2007) as well as Canada (Bolinder et al., 2007a). Table 3 shows r_{e_clim} values that can be used as starting points for using ICBM under different climatic conditions. If detailed climatic data are available, daily, monthly or annual r_e and r_{e_clim} can be calculated (Andrén et al., 2007).

Secondly, the annual input, i, is estimated as the sum of carbon inputs from the crop and manure. The approach we use for crop inputs is to apply allometric functions to yield data, that is, using estimates of the relations between crop yield, roots, stubble and straw (Paustian et al., 1990; Kuzyakov and Domanski, 2000; Bolinder et al., 2007b). Note that the allometric parameters can vary considerably within a plant species, for example, maize, depending on variety. Highly productive varieties grown under favorable conditions tend to have a high harvest index, that is, the proportion of grain to total above-ground biomass (Johnson et al., 2006). The annual C input (i) can never be exactly measured, and in some cases, it is best to optimize this parameter to obtain a good fit to available soil carbon measurements (within reasonable limits).

Thirdly, the humification coefficient, h, which determines the proportion of young soil C that becomes old soil C (humus) must be set. In the original ICBM paper (Andrén and Kätterer, 1997), how to estimate h using, for example, litter-bags was shown, and the default values to use when more detailed information is unavailable were also shown and exemplified as follows: crop residues about 0.12, manure about 0.35, and processed sewage sludge which is about 0.5. When manure or sewage sludge is added, a weighted average for h based on the relative inputs from manure and crop residues is used.

Parameters k_Y and k_O have usually not been changed, since they are multiplied by r_e in the model equations and thus, an increase in r_e can be balanced by a reciprocal decrease in k_Y and k_O (Figure 1). However, if the relative contributions of Y and O to total soil carbon mass at steady-state need to be changed, k_Y and k_O can be set to other values (Campbell et al., 2007).

Initial C mass in the topsoil is crucial for the outcome of the projections, if it is high, a decrease will be projected and if it is low, an increase will be projected. Since carbon mass is difficult to measure with high precision, it is sometimes better to modify the measured initial value to a value that fits the model projections, particularly, if the apparent changes between the initial and second sampling are unrealistic, for example, if the apparent increase in soil carbon mass is greater than the carbon added. The initial distribution between young and old C (Y_0 and O_0, Figure 1 and Table 2) can be set to the steady-state values calculated by the spreadsheet (Table 2). However, if the modeled period of time starts with, for example, an addition of mulch, Y_0 can be set to a higher value. Alternatively, if the modeling is preceded by a long period of black fallow, Y_0 can be set close to 0.

RESULTS OF USING THE ICBM MODEL FOR SOIL C PROJECTIONS WITH DATA FROM AGRICULTURAL FIELD EXPERIMENTS IN KENYA

If a rough estimate of the soil C balances in the experiment is wanted along with a projection of the development into the future, and only limited data is available (this would generally be the case regardless of

Table 3. Meteorological stations, sorted from N to S within a country, used for calculations of r_{e_clim}.

Country	Place	Latitude	Longitude	Altitude (m)	Mean temperature (°C)	Precipitation (annual sum, mm)	ET_o (annual sum, mm)	r_{e_clim}
Sweden	Karlstad	59° 24'N	13° 30'E	107	6.0	644.4	523.4	1
Sweden	Stockholm	59° 18'N	18° 03'E	44	7.0	542.2	595.1	1
Chad	Faya	18° 00'N	19° 10'E	234	28.4	6.5	5808.3	1.1
Senegal	Saint Louis	16° 01'N	16° 30'W	2	25.8	215.0	1746.2	2.3
Togo	Mango	10°,22'N	00° 22'E	145	27.9	1093.6	2163.5	4.3
Congo	Pointe Noire	04° 49'S	11° 54'E	17	24.9	1062.0	685.8	4.2
Congo	Brazzaville	04° 15'S	15° 15'E	314	25.3	1319.0	740.3	4.7
Kenya	Kalalu	0° 05'N	37° 10'E	2080	16.6	740.0	1254.5	2.2
Kenya	Matanya	0° 04'S	36° 57'E	1840	18.1	794.0	1493.7	2.1
Kenya	Muranga	0° 06'S	37° 00'E	1067	19.9	1083.0	1468.0	2.2
Kenya	Ahero	0° 09'S	34° 36'E	1200	22.5	1265.0	1730.0	4.1
Kenya	Kabete	01° 15'S	36° 46'E	1650	18.0	1069.8	1132.1	2.4

Country, station name, latitude, longitude, altitude (m), Mean annual temperature (°C), Annual precipitation (mm), Reference crop evapotranspiration (ET_o, mm), r_{e_clim}, which by default is normalized to 1 as the mean for the two Swedish stations, representing the calibration site (Revised from Andrén et al., 2007).

location), the analysis will be based on a mixture of data and rules-of-thumb. A medium-term comprehensive manuring experiment was performed at Machang'a (Embu), Mbeere District, Central Kenya, (0°47'S, 37°40'E; altitude1060 m and annual rainfall 730 mm), and the experiment was run between 1989 and 2002 (Kihanda et al., 2006). The experiment comprised several treatments but here we will concentrate on:

i. F, pearl millet/sorghum/cowpea/maize rotation, NPK fertilizer each year 1993 to 2002 (51, 12, 30 kg ha^{-1} of N, P and K respectively); '
ii. B1, earlier receiving of 5 tons goat manure per year, but after 1993, receiving no manure or fertilizer;
iii. C, a control receiving no fertilizer or manure.

The results from this experiment have been used in several model applications. The performance of the APSIM model was tested by Micheni et al.,(2004), and Century and RothC were evaluated for East African conditions using this data set (Kamoni et al., 2007).

The first step is to examine the measured soil C mass dynamics. Treatment C, which is unfertilized and not receiving manure, gave low yields and an average annual input of 0.71 tons carbon ha^{-1} (Kihanda et al., 2005). In spite of this very low input, soil carbon mass seemed to remain stable slightly above 10 t ha^{-1} (0 to 20 cm depth) after 1995 (Kamoni et al., 2007). The treatment receiving NPK fertilization (F) seems to be fairly close to steady-state with no clear trend with time and an average C mass around 15 t ha^{-1}. The manured treatment that had an increased carbon mass, 17 to 20 tons after four years of addition, reverted to about 15 tons after ca. 5 years (Kamoni et al., 2007). Thus, approximately, 10 t/ha seemed to be very stable or inert in this time span and we can tentatively set 10 tons as an inert pool, that is, excluding this from our calculations. Note that 'inert' does not mean that this pool never will decompose; it is assumed that it is inert in the 30-year perspective here. The soil carbon may be inaccessible through physical constraints (Feller and Beare, 1997) and/or chemically inert, such as charcoal (Glaser et al., 2002). Apparent differences in soil C mass between years are as high as over 2 tons (Figure 2) which partly can be due to differences in crop yields and thus, carbon input to soil between years and/or different weather conditions affecting decomposition in different years. However, estimates of soil carbon mass dynamics are based on field sampling followed by estimates of C concentration and bulk density and usually have a fairly low precision (Karlsson et al., 2003; Ogle et al., 2007), so an apparent difference may not be statistically significant. In fact, in the Machang'a experiment, no significant differences were found in soil carbon concentrations between two treatments receiving 5 and 10 tons manure ha^{-1} year^{-1}, respectively, during 1993 to 2003 (Kihanda et al., 2006).

Parameter r_e, which summarizes external influences on decomposition rates for Machang'a was estimated to be 2.1, based the calculated r_{e_clim} value for Matanya (2.1, 0° 04'S, 36° 57'E; 1840 m altitude and 794 mm annual rainfall) and Muranga (2.2, 0° 06'S, 37° 00'E; 1067 m altitude, 1083 mm annual rainfall) situated within 100 km from the Machang'a site (Andrén et al., 2007). Parameter r_{e_clim} is calculated assuming a degree of soil cultivation normal for Western European cereal production, that is, annual plowing of topsoil to 25 cm depth and harrowing etc. It is assumed that the degree of cultivation is the same here (manual hoeing to 20 cm is twice a year and set equal to plowing to 25 cm once a year), so no change

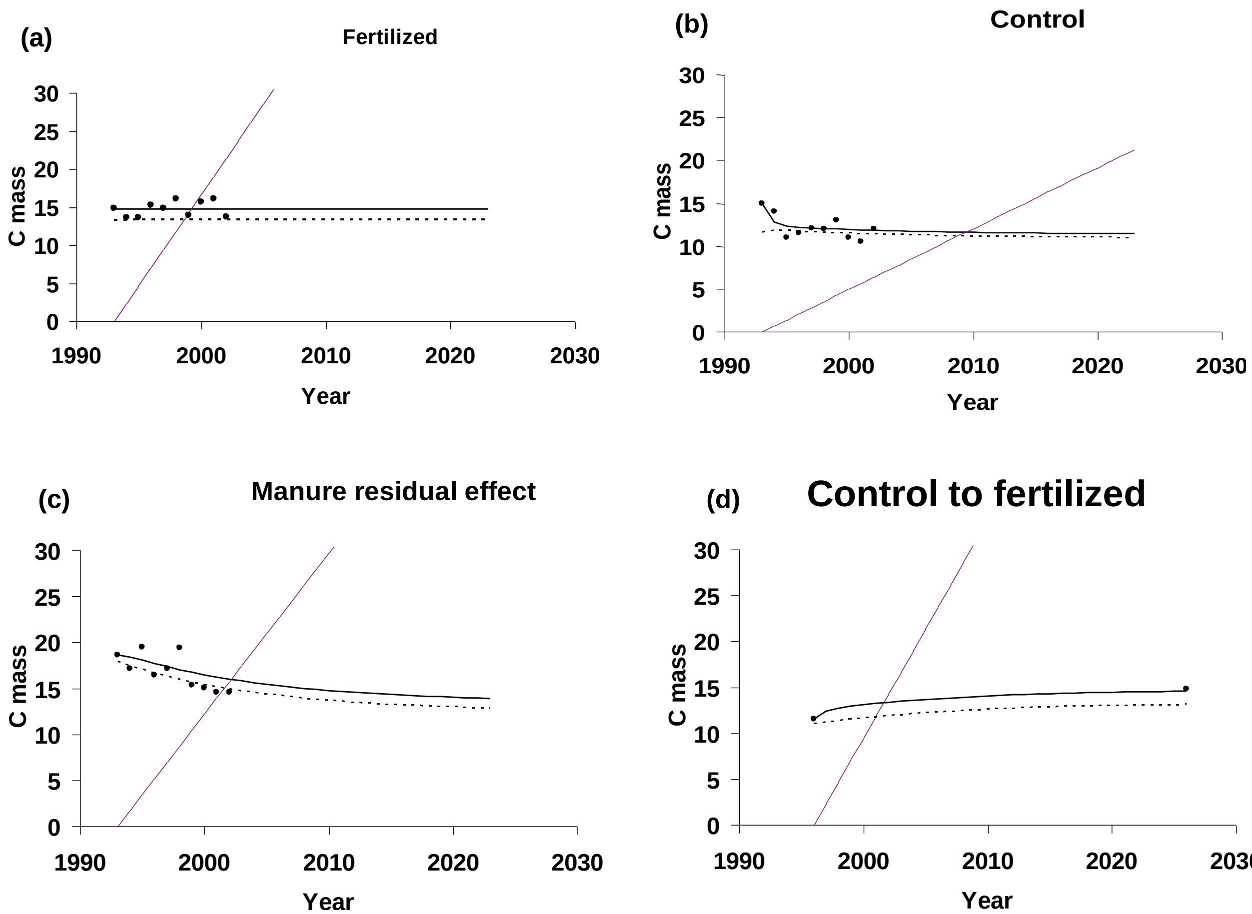

Figure 2. Measured data (black dots) and ICBM projections 1993-2023 (solid line=total C, dotted line=old+inert C, thin line=cumulative C input; the difference between the solid and dotted line indicates the young pool); of soil carbon mass (0-20 cm depth) in an agricultural field experiment in Kenya. Treatment 'Fertilized' was NPK fertilized annually; Treatment 'Control' received no fertilizer or manure; Treatment 'Manure residual effect' received no NPK fertilizer but had 1989-1992 been amended with 5 t ha-1 year-1 of goat manure; Imaginary treatment 'Control to fertilized',assuming the control from 1996 onwards became fertilized annually and that crop yields and carbon input became the same as in 'Fertilized'(the dot at year 1996 is the measured soil C mass in the control that year, and the dot at year 2026 indicate the steady-state value for treatment F).

was made. The soil water storage capacity, that is, the difference between water content at field capacity and that at wilting point will affect water content and also the activity. For the soil used in this example for r_{e_clim} calculations, the difference is 13.5% by volume, and for the soil in this experiment, it is 12% (DUL-LL15, Table 2) (Micheni et al., 2004). We assumed that this small difference was not affecting the overall activity in the soil. Also, the original r_{e_clim} was calculated assuming no crop cover, which results in no transpiration and more water left in the soil and thus a slightly higher activity. Therefore we reduce r_e slightly to 2.1. The humification quotient, h, indicating the quality of the input plant residues, is set to 0.12 according to the default values for plant residues. Calculating annual carbon inputs from plants to soil can be a complex process (Paustian et al., 1990; Kuzyakov and Domanski, 2000; Bolinder et al., 2007b). In this experiment, all plant residues except the harvested grains were returned to the respective plots at the end of every growing season (two crops/year), and the above-ground dry matter yields were very variable between years, ranging between 0 and 12 t ha^{-1} (Micheni et al., 2004), and grain yield showed a similar variability, ranging between 0 and 4 t ha^{-1} (Kihanda et al., 2006). Here, we used the already calculated values for annual C input, namely, 2.38 tons for F, 0.71 tons for C and 1.75 t ha^{-1} $year^{-1}$ for treatment B1 receiving no NPK (Kihanda et al., 2005). Starting with treatment F, we have obtained parameters as listed in the top row of Table 4, with one exception, k_O. This parameter had to be adjusted, since the default value 0.006 $year^{-1}$ represented a Swedish clay loam soil and was based on an analysis assuming

Table 4. Parameter values used in the ICBM model.

Parameter	*i*	*h*	r_e	Y_0	O_0	C_0	C_{30}	C_{ss}
Fertilized	2.38	0.12	2.1	1.42	3.35	4.77	14.77	14.77
Control	0.71	0.12	2.2	3.36	1.64	5.00	11.42	11.35
Manure res.	1.75	0.12	2.1	0.71	7.93	8.64	13.90	13.48
Fertil. Contr.	2.38	0.12	2.1	0.40	1.10	1.50	14.56	14.74

Parameter descriptions are as used in Table 1. C_0 = total initial C mass (t ha^{-1}), C_{30}= Projected C mass after 30 years, C_{ss}= Projected C mass at steady-state. Treatments in the experiment in Kenya (Kamoni et al., 2007): 'Fertilized' = Treatment *F*, receiving NPK fertilizer; 'Control' = *C*, not fertilized or manured; 'Manure res.' = B1, residual effects of earlier annual applications of 5t manure. 'Fertil. Contr.' = Modelled using the assumption that Control from 1996 onwards received fertilizer as Fertilized. Note: In all treatments, an inert fraction of 10 t ha^{-1} was excluded from the modeling (thus the total initial C in the top row was measured as 14.77), but added back to the final results for C_{30} and C_{ss}. In all treatments, k_Y and k_O, were set to 0.8 and 0.041, respectively.

no inert pool. As discussed earlier, the Machang'a dataset seems to reflect that a significant fraction of the soil C pool was inert. Thus, the value of k_O calibrated under Swedish conditions did not seem valid for the conditions at Machang'a. Therefore, we optimized for the average value of all measurements assuming treatment F represents steady-state and reach the value for k_o = 0.041, or 6.8 times higher than the original k_O.

The initial mass of non-inert carbon in the soil was set to the average of the measured values (4.77 tons) and the initial amount of young carbon was set to the amount at steady-state, calculated by the spreadsheet (1.42 tons). The results are not very surprising such that the model indicates that this treatment is in steady-state (Figure 2a and b).

However, applying basically the same parameter set to the control (C) treatment may reveal if the assumptions made are suitable. We only change the input to 0.71 tons (Table 4) and since there is very little crop growth, and transpiration, we change r_e back to 2.2 (description of r_{e_clim} *is* in the foregoing). If accepted that the observations indicate a rapid decrease from 1993 to 1995 (possibly because of large earlier inputs) and thereafter, a small decrease, we can try to emulate this. We can set O_0 to the average between 1995 and 2003 (1.64 tons, since we have assumed that we have 10 tons of inert C). Then, we can set Y_0 as the difference between the 1993 observation and O_0. Thus, we assume that the earlier unknown conditions have resulted in a large input of fresh plant material. The results (Table 4 and Figure 2a) mimic the initial results fairly well, and indicate a steady-state mass of 11.35 tons, with a slow decline towards this value. Note that the low input rapidly reduces the *Y* fraction to less than 0.5 tons (Figure 2b).

To model the treatment that had earlier received 5 tons manure annually and had a higher soil C mass, we reduce the input to 1.75 tons and use the initial measured value (18.64 tons in total and 8.64 when inert fraction excluded) as starting point. The other parameters remain the same as in the F treatment. The higher initial C mass and the lower input result in a decreasing trend (Figure 2c), and a steady-state value of 13.48 tons, and after 30 years we would expect the soil C mass still to be slightly higher than that (Table 4). We could, however, assume that Y0 was somewhat higher due to the earlier input, and if we set that proportion higher, the simulated decrease will be more rapid initially (not shown).

We can also perform a "what-if" experiment. Let us assume that the control in 1996 had been changed to the same fertilizer regime as that in the fertilized treatment, and that the crop immediately responded so that the carbon input became similar to that in the fertilized treatment. Thus, we use the 1996 carbon mass from the control, and *i* and r_e from the fertilized treatment (Table 4). We assumed that the initial mass in 1996 was the measured as 11.50 kg (including 10 kg inert carbon) and that the young pool was in steady-state, 0.4 t ha^{-1}. The increase in annual input rapidly increases the young pool, while the old pool increases more slowly (Figure 2c and d). After 30 years, however, the control almost reached a steady-state level for the fertilized treatment (black dot at year 2026). This also illustrates the amount of the extra input that was lost and which did not really contribute to soil carbon mass; after 10 years the increase in soil C is only 2.25 tons (Figure 2), but the extra added crop residue C is 16.7 tons (10 years of 2.38 minus 0.71 tons extra input).

DISCUSSION

A reasonable question is whether a model developed for a cold temperate climate is valid in a tropical climate. In principle, the r_e parameter and the functions used to calculate activity in the soil from temperature and water conditions should compensate for differences in climate, and these functions are not unique for this model (Andrén et al., 2007). However, the data set from Kenya used here clearly indicates that including, or rather excluding an inert fraction was necessary. The original estimate of

k_O was made using data from a long-term black fallow on a clay loam soil in Sweden (Andrén and Kätterer, 1997), assuming no inert fraction. Later investigations based on the same data set suggested that a better fit to additional isotope measurements would be obtained by assuming 50% inert soil carbon (Petersen et al., 2005). This would mean that to obtain the observed dynamics, k_O has to be increased, and in the current application with a major fraction apparently inert, the best fit was obtained with a much higher k_O than that initially used. This raises an issue related to inert carbon in modeling soil C dynamics in African systems, and this issue seems pertinent for all soil C models, not just ICBM. Importantly, the size of the inert C pool is reasonably estimated on a particular site to soil C modeling in Africa? Here, this study's assessment of the Machang'a dataset suggested a 10 t ha^{-1} inert pool, which is a large fraction of the initial soil C used in the simulations (~ 55%).

In the APSIM model application to the Machang'a dataset, the authors assumed a similar fraction of inert C from the initial soil carbon measurement (Micheni et al., 2004). However, the RothC application to the Machang'a data assumed only a 3 t ha^{-1} inert pool (Kamoni et al.. 2007). In a European application, the modelers demonstrated a high sensitivity of soil C model predictions to the initial assumption on the inert content in soil C measurements (Puhlmann et al., 2006). Our results here support that same idea, where we had to change the value of k_O to accommodate different assumptions on the initial size of the inert pool. It is therefore, our opinion that this issue has not (to date) received enough attention in the literature regarding modeling soil C dynamics in long-term African datasets. If this parameter can be estimated by chemical analysis, it would certainly help support modeling assumptions and to reduce uncertainties in calibrated model parameters. The importance of these stable C fractions on soil C dynamics could also have land-use management applications, particularly, with regards to the production and use of biochar as soil fertility amendments.

In the study of Kamoni et al. (2007), simulation results were presented using both RothC and Century for three of the different experimental treatments at Machang'a. In general, the long-term trends in the observed data were simulated acceptably, but neither of the models captured inter-annual variations very well. It should also be noted that the long-term trends in the Machang'a dataset are not very dynamic in any of the treatments (either flat or gently sloping SOC trends) and as such, simulating the long-term trends in this dataset by itself does not provide strong evidence of a model's capabilities (including ICBM). It is our intent to develop more general parameter sets for ICBM that will be useful for a wide variety of regional conditions in Africa. The preliminary results presented herein suggest a strong potential for ICBM, with its simple and easily accessible model structure, to provide rapid and accurate predictions of long-term SOC dynamics. However, future investigations are required (and ongoing) to achieve this. For example, we intend to calculate the simple climate index from a large number of African weather data sets, using the already developed methodology (Andrén et al., 2007). There have also been speculations and calculations regarding the possibility that decomposition *in situ* of roots is lower than measured on roots sampled from soil, and that the *h* values would be considerably higher than earlier believed Kätterer et al. (2011). In principle, we can use different *h* values for roots and shoots, but we lack sufficient data so far. If root *h* has been underestimated, this may help to explain, for example, the minor effects of adding cut bush material to plots as reported by Gentile et al. (2010).

As observed in the foregoing, we touched on the issue of uncertainty as related to parameter values in a model and the influence that this can have on future predictions. Recognition of uncertainty in soil C modeling, and all environmental models in general, is receiving increased attention in the scientific literature. In our analysis here, there are uncertainties in estimates of soil C inputs, soil SOC dynamics, climatic conditions, modeling assumptions such as the assumed size of the inert pool, and model structural errors, none of which are acknowledged in our presentation of predicted (future) trends. This is entirely typical of the majority of soil carbon modeling efforts, both in Africa and worldwide, although, some efforts have recently been made to quantify uncertainties (Ogle et al., 2006, 2007).

There are also numerous unaccounted processes that can contribute to uncertainties in interpreting modeling results. For example, the Machang'a dataset did not show a statistical significant response in soil C in the 10 t ha^{-1} $year^{-1}$ manure treatment compared to the 5 t ha^{-1} $year^{-1}$ (Kihanda et al., 2005). This of course, is a difficult scenario to reproduce in any soil-C model, but perhaps the "real" reason in the field may have been related to a "saturated" soil response leading to rapid decomposition (Stewart et al., 2007), or rain-induced outwash of manure on the soil surface, or earthworm or dung beetle populations have increased and buried manure below sampling depth or termites have carried manure out of the plots (Brussaard et al., 2006), or that the high rates of manure applied increase water storage capacity and thus increased r_e. In recent years, there have been significant advances in the field of uncertainty analysis, many of which have occurred in the field of hydrological modeling (Todini, 2007). There are now numerous Monte Carlo methods for uncertainty analysis that can be used to explicitly quantify uncertainty in parameter values and predicted time series. We strongly advocate the use of uncertainty analysis, such as the GLUE methodology (Beven and Freer, 2001), and we will be using this tool ourselves in the future with ICBM.

The typical result of model calibration with uncertainty analysis is the representation of model parameters as distributions, rather than single point values, and time history predictions as credibility bands, rather than single line projections. Without explicit recognition of uncertainties, the true needs for better datasets and for models with appropriate levels of functionality can be easily overlooked (Pappenberger and Beven, 2006). The uncertainty analysis may also help in formally evaluating how complex models are warranted given the precision of the available data – and the truth of the bold statements given in the study's introduction may be revealed.

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