Comparative Application of APSIM, RothC and Century to Predict Soil Carbon Dynamics

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Abstract: Soil carbon models will likely play a vital role in national carbon accounting systems. In this study, three models (APSIM, Century and RothC) are used to simulate soil carbon dynamics under the same agro-ecological conditions and management practices. These models are widely-used in Australia, differ in time step and also in how they represent the crop-soil system. APSIM provides a framework whereby a cropping system model is configured from component modules, which operate on a daily time step. The Century model has soil organic matter, water budget, grassland/crop, forest production sub-models and management and event scheduling functions operating on a monthly time step. RothC models the turnover of organic carbon in non-waterlogged soils, taking into account clay content, temperature and moisture content. It operates on a monthly time step. Because RothC has no crop growth routine we used APSIM's crop model outputs to provide plant residue, yield and root data for RothC. The three models are run for six sites in Southern Queensland and statistical analyses are carried out to evaluate and compare model performances in soil carbon estimations. All models provide a satisfactory representation of the pattern of soil carbon decline under continuous cultivation and possible reasons for differences in model behaviours are also discussed. The sensitivity analysis shows that Century is less sensitive to initial soil C levels than the other two models.

Keywords: APSIM; Century; RothC; Soil carbon modelling; Sensitivity and Statistical analysis

1. INTRODUCTION

A number of soil organic matter models have been developed to monitor soil carbon changes and subsequent feedback effects when soil management practices are changed. In Australia, soil organic matter (SOM) models such as Century [Parton et al. 1987] and RothC [Jenkinson, 1990] are widely used in research. The locally developed crop production modelling shell, APSIM [Probert et al. 1998] also has the capability to simulate soil carbon dynamics. Comparison of SOM models may be used to select an appropriate model for a particular application. This paper describes the behaviour of these three modelling systems in relation to experimental observations from long-term trials carried out in southern Queensland.

2. SOIL CARBON MODELLING

2.1 Introduction

Soil organic matter includes plant and microbial residues in all stages of decomposition. Each soil carbon model is discussed briefly in terms of treatment of soil carbon dynamics, required inputs and time step of the simulation.

2.2 APSIM

APSIM (Agricultural Production System sIMulator, Version 2.0) is a modelling framework that allows models of crops, pastures, trees, soil water, nutrients, and erosion to be flexibly configured to simulate diverse production systems. Most modules, including SoilN and Residue that represent turnover of organic matter, operate on a daily time-step. APSIM distinguishes between surface residues and residues in the soil. Within SoilN, organic materials are conceptualized as fresh organic matter (FOM) and two soil organic matter pools (BIOM and HUM) that differ in their rates of decomposition [Probert et al., 1998]. The BIOM pool notionally represents the more labile, soil microbial biomass and microbial products, whilst the HUM pool comprises the remainder of the soil organic matter. The amount of inert C represents as a fraction of soil C. Flexible specification of management regimes in farming systems is possible. The timing and nature of operations such as sowing, tillage, residue management, fertilization, crop rotation, irrigation, grazing and harvest methods are all controlled by a user defined script language. The minimum climate data set required to run are daily maximum and minimum temperature, radiation and rainfall. Information on soil texture per se is not an input to the model although other parameters are used which generally correlated with soil texture.

2.3 RothC

RothC (Rothamsted soil carbon turnover model) models the turnover of organic carbon in non-waterlogged soils [Jenkinson, 1990], using monthly time steps and can model out to 100,000 years to find the soil's conceptual 'equilibrium state'. A spreadsheet implementation of RothC-26.3 was used. The CSIRO in Adelaide and the Australian Greenhouse Office have enhanced the spreadsheet version of RothC to include the ability to use the historical weather time series rather than average weather and the radiocarbon dating computations.

Plant material enters the soil environment, as readily decomposable plant material (DPM) and intermediate resistant plant material (RPM), and undergoes decomposition through the soil microbial biomass to form a number of pools: inert (IOM), slow humic (HUM) and biomass (BIO). These pools have varying resistance to degradation. RothC considers all soil carbon transformations to occur in a single soil layer. As RothC does not contain a sub-model for plant production; plant residue inputs are either measured directly or are estimated from crop yields. In this study, residue inputs, yields and root weights were taken from APSIM simulations.

2.4 Century

The Century (version 5) agroecosystem model is the latest version of a soil organic model initially developed by Parton et al. (1987). This model simulates C and nutrients (N,P,S) dynamics on a monthly time step for an annual cycle over time scales of centuries and millennia. The minimum climate data required to run are monthly maximum and minimum temperature and rainfall. Soil texture in terms of sand, silt and clay content is an input to the model. The SOM sub-model includes three soil organic matter pools (active, slow and passive) with different potential decomposition rates, above and below ground litter pools and a microbial pool which is associated with decomposing surface litter.

Plant production can be simulated by using grassland/crop, forest or savanna system sub-models and land use change can be represented by changing the plant production type during model runs. Simulation of complex agricultural management practices including crop rotation, tillage practices, fertilization, irrigation, grazing, and harvest methods are possible.

2.5 Approximation of pool sizes

Many organic compounds in the soil are intimately associated with inorganic soil particles. Physical fractionation techniques that relate more directly to soil carbon dynamics are often used to define and delineate various relatively-discrete soil organic carbon pools [Post and Kwon, 2000]. Figure 1 shows the major physically separated soil carbon fractions that can be related to carbon pools.

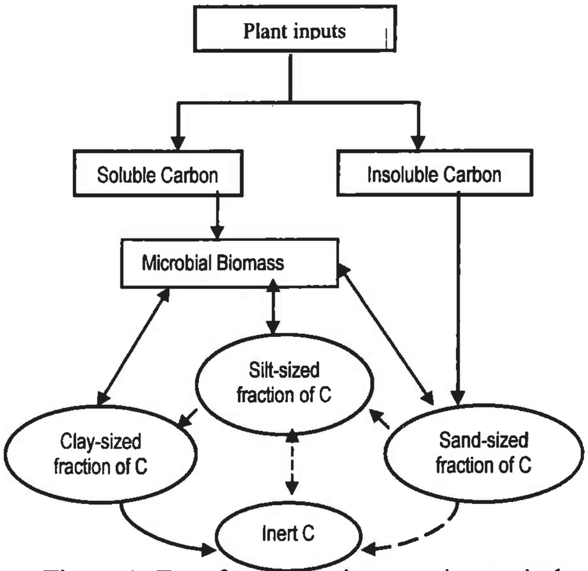

Figure 1. Transfer of organic matter in a typical soil carbon model.

In this study, initial sand-sized fraction of C is considered to be the active pool in Century. Clay-sized fraction of C after a considerable period of cultivation is taken as the passive pool in Century and IOM in RothC. Then the difference is taken to be the silt-sized fraction of C as the slow pool in Century and HUM pool in RothC. The BIO pool in RothC is estimated as 20% of total soil C [*pers. comm.* Skjemstad, 2001]. Since there is no recommended method to estimate inert C in APSIM, an assumption has been made that the inert C increases logarithmically with the soil depth reaching a maximum at 1m. Values for BIOM in APSIM are assumed to be 0.06, 0.04 and 0.03 of total soil C for 0-10cm, 10-20cm and 20-30cm layers respectively.

3. LONG-TERM EXPERIMENT

Simulations were conducted for six sites in southern Queensland subject to continuous wheat cropping with a range of commencement dates; 1910 for Waco (Wa), 1935 for Langlands-Logie (L-Logie), 1945 for Cecilvale (Ce), 1955 for Billa Billa (Bi), 1957 for Thallon (Th) and 1960 for Riverview (Rv). The location of study area, description of soils, crop and soil management practices, and soil sampling, analytical techniques as well as clay- and sand-sized fractions of soil carbon data were given in a series of papers by Dalal and Mayer [1986a,b and c]. In this study, each model was used to simulate carbon (C) dynamics in the 0-20 cm soil layer. Initial soil carbon data for the top 20cm were taken from the same sources. Soil and soil C data and management practices relevant to the modelling exercise were extracted from Dalal and Mayer [1986a,b and c] and are given in Table 1. Information on soil physical properties is assumed to be constants over time.

The planting decision and planting time in APSIM were set with respect to amount of rainfall received since no information was available on planting times. If a minimum rainfall (25mm) was not received in consecutive 10 days of the planting season, no sowing was assigned in APSIM. Any fallow years identified in APSIM was also taken to the Century scheduling, as fallow years were not always recorded.

4. COMPARISON AND EVALUATION OF MODEL PERFORMANCE

Models were evaluated in terms of their ability to simulate observed soil carbon changes. The total difference between the simulated and measured values was calculated as the root mean square error, RMSE (%). The modelling efficiency (*ME*) provides a comparison of the efficiency of the chosen model with the efficiency of describing the data as the mean of the measured data. The coefficient of determination (*CD*) is a measure of the proportion of the total variance in the measured data that is explained by the simulated data. The bias in the total difference between simulation and measurements was determined by calculating the relative error, *E*. The nature of the bias was further examined using the mean difference, *M*. The mean difference between measured and simulated values gives an indication of the bias in the simulation, but is less informative than *E* because errors are not proportional to the size of measurement. However, it is a useful statistic when standard error values are not available to derive a value for $E_{95\%}$ since *M* can be related directly to the *t* statistic to show a significant difference between simulated and measured values. A *t* value greater than the critical two-tailed 2.5% *t* value was taken to indicate that the simulation showed a significant bias towards over- or under-estimation when compared to measured values. To assess whether simulated values follow the same pattern as measured values, the sample correlation coefficient (*r*) was calculated. The value of *r* is useful in assessing how well the shape of the simulation matches with the shape of the measured data.

Table 1. Soil data and crop management information.

	Waco	L-Logie	Cecilvale	Billa Billa	Thallon	Riverview
Clay %	72	49	40	34	59	18
SC %	1.40	1.85	1.42	1.26	0.73	1.03
BD	0.90	1.09	1.10	1.00	1.02	1.24
Soil pH	8.1	7.4	7.4	7.4	7.2	6.5
CN ratio	11.2	11.0	13.1	10.6	12.1	14.8
SR %	51	23	33	27	36	86
N fert	32.0	7.5	18.3	5.0	5.0	5.0
P fert	1.0	0.0	7.7	2.0	0.0	0.0
NC	5	4	5	5	3	3

(SC = initial soil carbon for top 20cm, BD = bulk density (Mg m^{-3}), CN ratio = CN ratio of the soil, SR = amount of stubble removed, N fert = amount of nitrogen fertilizer (kg/ha year), P fert = amount of phosphorus fertilizer (kg/ha year), NC = average number of cultivations per year).

These statistics can be useful in assessing how well the shape of the simulation matches the shape of the measured data. Further information of this statistical analysis can be found in Smith et al. [1997].

Initial C level when virgin soils are brought under cultivation generally decline with the time [Dalal and Mayer 1986b]. Sensitivity analyses are performed in this study to assess how the initial soil C level is important to predicted soil C. The following dimensionless index of sensitivity (*SI*) is used for sensitivity analysis:

$$SI = \frac{{R_1 - R_0}/{R_0}}{{P_1 - P_0}/{P_0}} \qquad (1)$$

where R_1 is predicted soil C when the initial soil C is set to P_1, R_0 is default predicted value of initial soil C, P_1 is 1.1 times default soil C value, and P_0 is default soil C value. A sensitivity index of 1 indicates that the predicted soil C changed by an average of 10% for a 10% change in the initial soil C.

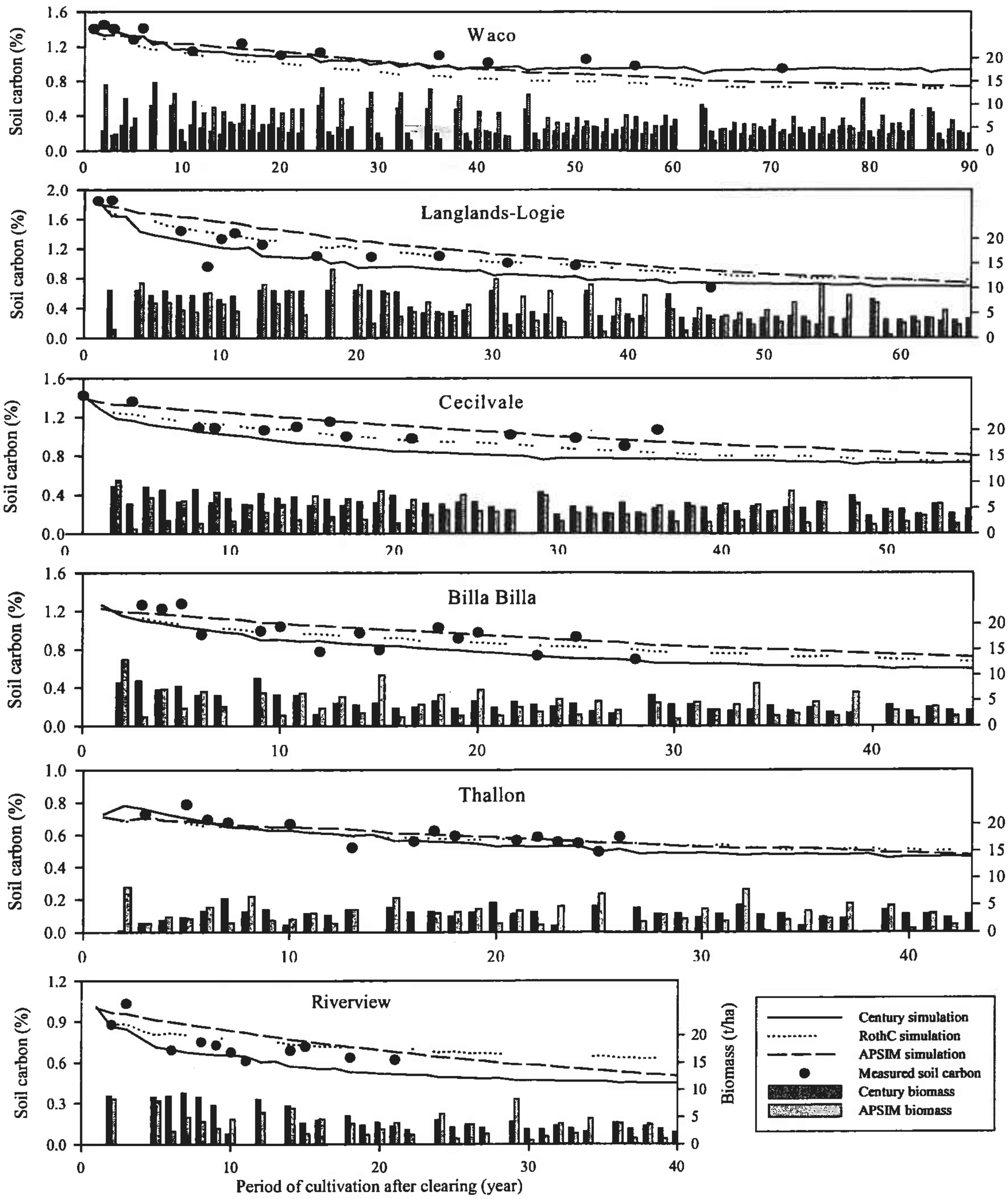

Figure 2. Changes in soil carbon in the top layer (0-20cm) with the period of cultivation. Simulated above-ground biomass production by Century and APSIM is also shown.

5. RESULTS AND DISCUSSION

Figure 2 shows the simulated run-down curves against measured soil carbon data for each model as well as for each site and simulated above-ground biomass productions for APSIM and Century models for each site. Simulated biomass outputs from both APSIM and Century are in reasonable agreement, however, no measured data were available to verify the simulation. It is not known how fertilization and other treatments may have affected biomass production and yields. Plant diseases may also have influenced crop growth and yield in some seasons, but such effects are not included in the models. For all three models, the total soil C in the surface 0-20 cm has declined continuously at all sites with a tendency to approach a steady state, though all models and sites show that the approach to an equilibrium is slow (Fig. 2). The consequences of fallow years in terms of rapid soil C decrease are more clearly shown in simulations with Century than with the other two models. Much of the continuous soil C losses can be attributed to reduced inputs in organic matter, increased decomposibility of crop residues and tillage effects that decrease the amount of physical protection to decomposition [Post and Kwon, 2000].

Table 2. Decline in soil C as a percent of total C for the first 40 years after clearing

	Waco	L-Logie	Cecilvale	Billa Billa	Thallon	Riverview	Average
Century	32	58	47	53	37	56	47
RothC	41	51	44	45	32	39	42
APSIM	31	47	35	39	32	50	39

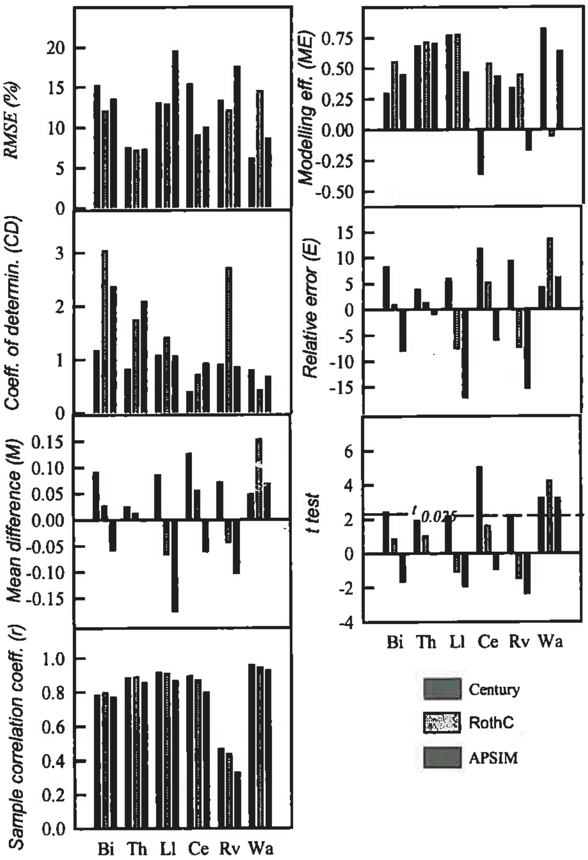

Figure 3. Graphical representation of Statistics describing the performance of models

The decline in soil C over the first 40 years since clearing (Table 2) is steepest with Century simulations followed by RothC and APSIM respectively with the exception of Waco where RothC shows the steepest decline and Riverview where APSIM's shows more steep decline than RothC. There appears to be a large effect of N fertilizer when combined with stubble retention (32 kg/ha of N fertilizer and 51% stubble retention, Table 1) in the Century simulation for Waco, a response not matched in APSIM. This may explain that the combined effect of N fertilizer and stubble retention is greatly represented in the century than in APSIM [Probert et al. 1995].

Figure 3 explains the statistics describing the performance of models. All three models have values of total error (*RMSE*) around 8-18% and the averaged value of *RMSE* for all sites is 11.6% for Century, 11.2% for RothC and 12.6% for APSIM. Century and APSIM had highest total error at two locations each and RothC was highest for one location.

Since standard errors of the measurements were not available, the statistical significance of *RMSE* could not be assessed. Therefore, the accuracy of the simulation was assessed by calculating the modelling efficiency (*ME*) and the coefficient of determination (*CD*). Each model has one negative *ME* that indicates that the simulated values describe the data less well than a mean of the measurements. Except for these three negative values, the positive values of *ME* are distributed within the same range. A positive value indicates that the simulated values describe the trend in the measured data better than the mean of the measurements. A *CD* value 1 or above indicates that the deviation of the predictions from the mean of the measured values is less than that observed in the measurements, i.e. models describe the measured data better than the mean of the measurements. Values of *CD* vary with the site as well as with the model. Values of *CD* equal to or greater than 1 occur at four locations for RothC, three locations for APSIM and two locations for Century.

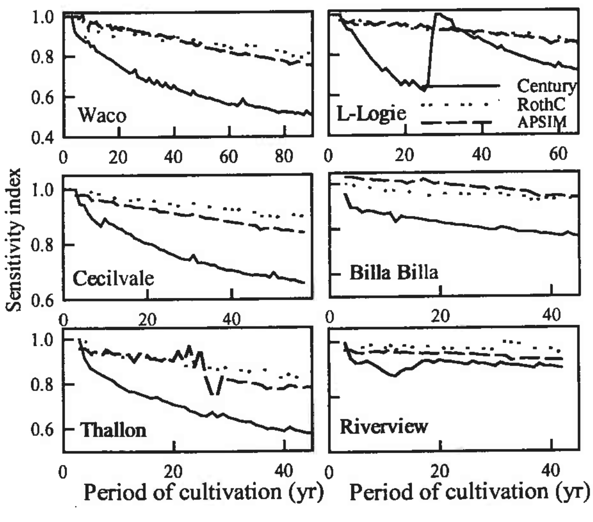

Figure 4 Sensitivity analysis for initial soil C levels

In terms of model bias, values of *E* and *M* rank model bias similarly and the highest values of *E* and *M* have found two occasions in the Century, two occasions in APSIM and one occasion in RothC. The *t* values for *M* indicate that there were four significant biases in which two for the Century and one each for other two models. However, RothC showed the lowest overall bias. All models have a significant bias on Waco. All models showed positive correlations (r) between measured and simulated data. The Century has highest values on four occasions whereas RothC had two.

Sensitivity indices (SI) in Figure 4 show that, for all models at all sites, except Century at Langlands-Logie, the sensitivity to initial soil C levels decreases over the period of cultivation. This occurs because the difference in predicted soil C between the default and increased values of initial soil C declines over the period of cultivation. Values of SI for RothC and APSIM behave in a fairly similar manner. However, in Century, SI values have declined more rapidly than for the other two models. This may be caused by a relatively rapid adjustment of pool sizes in Century.

6. CONCLUSIONS

All models provide a satisfactory representation of the pattern of soil carbon decline under continuous cultivation. Total error between measured and simulated values was moderately low (5 < RMSE > 20) for all models. The values of modelling efficiencies and coefficients of determination are shown to be in a fairly similar range for all sites. In terms of bias, RothC behaved somewhat better than other two models. All models show a positive correlation between measured and simulated data. Despite some statistical differences in soil C outputs of three soil carbon models, all three models may be used to effectively and accurately simulate soil carbon dynamics at the test sites. The sensitivity analysis shows that Century is less sensitive to initial soil C levels than other two models.

One of the major concerns in this modelling exercise was the level of site-specific information required. This is only a concern depending on the intended use. Since RothC requires less site specific information and basic inputs, and is less complex, it is well suited to simulations where information is limited or operations must be conducted on spatial arrays. However, independent systems for estimation of plant residue inputs are needed. As Smith et al. (1997) stated, differences in the level of calibration are likely to be partly responsible for the differences in model performance. However, in this study, all of available soil and management information have been employed wherever possible in model calibration.

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