Confidence in soil carbon predictions undermined by uncertainties in observations and model parameterisation

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Abstract

Soil carbon (C) responds quickly and feedbacks significantly to environmental changes such as climate warming and agricultural management. Soil C modelling is the only reasonable approach available for predicting soil C dynamics under future conditions of environmental changes, and soil C models are usually constrained by the average of observations. However, model constraining is sensitive to the observed data, and the consequence of using observed averages on C predictions has rarely been studied. Using long-term soil organic C datasets from an agricultural field experiment, we constrained a process-based model using the average of observations or by taking into account the variation in observations to predict soil C dynamics. We found that uncertainties in soil C predictions were masked if ignoring the uncertainties in observations (i.e., using the average of observations to constrain model), if uncertainties in model parameterisation were not explicitly quantified. However, if uncertainties in model parameterisation had been considered, further considering uncertainties in observations had negligible effect on

uncertainties in SOC predictions. The results suggest that uncertainties induced by model parameterisation are larger than that induced by observations. Precise observations representing the real spatial pattern of SOC at the studied domain, and model structure improvement and constrained space of parameters will benefit reducing uncertainties in soil C predictions. The results also highlight some areas on which future C model development and software implementations should focus to reliably infer soil C dynamics.

Keywords: carbon cycle, carbon sequestration, measurement uncertainty, model optimisation, prediction uncertainty

1 Introduction

Integrated approaches such as process-based mechanistic models are increasingly used to systematically explain, explore and predict responses of natural and human-managed systems to environmental changes (Holzworth *et al.*, 2015, Laniak *et al.*, 2013). Under changing environmental conditions such as global warming and land management change, soil carbon (C) dynamics is particularly important as its core role in determining C and nutrient cycling in terrestrial ecosystems and the relevant environmental footprints. Soil C models are the only reasonable approach available for assessing soil C dynamics across spatiotemporal scales and for understanding mechanisms underpinning soil C stability under various environments (Friedlingstein *et al.*, 2006, Thornton *et al.*, 2007). In order to use these models to design effective management strategies, it is vital to understand the confidence level in model performance (Bennett *et al.*, 2013, Kelly (Letcher) *et al.*, 2013). A number of studies have recognised that reliability of model predictions must be carefully assessed due to uncertainties in model inputs, model parameters and structure, and scaling of model outputs etc. (Clifford *et al.*, 2014, He *et al.*, 2014, Luo *et al.*, 2013, Ogle *et al.*, 2010, Post *et al.*, 2008, Xia *et al.*, 2013). An additional source of uncertainty comes from the spatial variability in soil C measurements that are used to constrain soil C model, and has not been explicitly

quantified in current soil C modelling.

Most soil C models divide soil C into several conceptual pools with different decomposability, and simulate decomposition of each pool by first-order kinetics (Smith *et al.*, 1997). Some of the pools cannot be directly measured and there is no agreed process to initialise these pools with bulked measurements of total soil C. As a result, derivation of the decomposition rate of those pools is constrained by local observed data of total SOC. The common practice is to derive a single set of model parameters that enables a good match between simulated soil C and the average of measured soil C (based on different replicates) at given time. Such constrained models are then used to predict possible soil C changes under different management practices across environments (Grace *et al.*, 2006, Li *et al.*, 2003, Lugato *et al.*, 2014, Todd-Brown *et al.*, 2014).

Such predictions are subject to unknown uncertainties. Firstly, uncertainty in initialisation of soil C pools interacts with uncertainty in derived decomposition rates. For example, similar model performance can be achieved either by optimising decomposition rates or by partitioning total soil C to different conceptual pools with different decomposition rates. Secondly, inaccuracy and/or variability in bulked measurements of total soil C further impact on initialisation and parameterisation of the model. As a result, model initialisation and parameterisation become very sensitive to the data that are used for model constraining (Hararuk *et al.*, 2014, Juston *et al.*, 2010, Keenan *et al.*, 2012, Xenakis *et al.*, 2008; Ogle *et al.*, 2010, Weng & Luo, 2011). Even at the field scale, great spatial variability exists in soil properties including soil C (Cambardella *et al.*, 1994). For example, Zhou *et al.* (2008) demonstrated that soil C varied strongly spatially and its spatial autocorrelation only occurs in ~2 m of distance in a grazed grassland. Todd-Brown *et al.* (2013) have suggested that uncertainty in bulked measurements of soil C content must be integrated with errors involved in extrapolating data from individual soil profiles to the regional scale. This spatial variability

makes it difficult, if not impossible, to derive the real estimate of average soil C for model initialisation and/or parameterisation based on limited samples.

To date, however, most of studies focused on uncertainty in model inputs in terms of limited availability of a specific data source (e.g., edaphic characteristics at higher resolution, and information on land use and management) that is needed to initialise and/or parameterise model (Falloon *et al.*, 2011, Luo *et al.*, 2013). Some other studies also addressed the effect of data derived from different environments on model parameterisation thereby model outputs (Hararuk *et al.*, 2014, Juston *et al.*, 2010). In this study, we used a process-based biophysical model, the Agriculture Production Systems sIMulator APSIM (Holzworth *et al.*, 2014, Keating *et al.*, 2003), together with a long-term soil organic C observational (measured 20 times during a 25-year experiment) dataset, to quantify: 1) the potential uncertainty in soil C predictions caused by model initialisation and parameterisation, and 2) the additional uncertainty caused by variation in soil C measurements that are used for model initialisation and parameterisation. For the latter, variation in replicates for each of the 20 observations during a 25-year agricultural experiment were investigated when using the data to constrain the model. The results can provide insights into collection of effective data sets for model constraining and development of next generation models.

2 Materials and Methods

2.1 Study site and data source

Field experimental data collected by the Wagga Wagga Agricultural Institute of NSW Department of Primary Industries was used in this study. The experimental site was located at the Wagga Wagga, New South Wales, Australia (35.11°S, 147.37°E). It has a temperate climate with uniform rainfall distribution across the year. Mean annual temperature was 15.9°C and mean annual rainfall was 538 mm. The soil is a chromic luvisol, and the site was

maintained as an annual pasture for 19 years from 1960 to 1978, except for a crop of lupins (*Lupinus Angustifolius*) in 1975 and oats (*Avena Sativa*) in 1976. The surface 10 cm soil was a clay loam with 29% clay, 15% silt and pH 4.9 in 1979. Data collected under two treatments, continuous wheat with (100 kg N ha⁻¹ yr⁻¹, N100) and without nitrogen (N0) fertilizer application, were used for this study. In both treatments, residue was burned, and soil organic C content (%) in the 0–10 cm soil layer was observed 20 times for each treatment from 1979 to 2004, each time with five or up to 12 replicates for each observation (Fig. 1). Soil bulk density was also measured along with the measurement of soil C content, and they were used to calculate soil C stock (t ha⁻¹). More detailed information on experimental design, soil sampling strategy, land use, soil conditions, management and observations for this experiment can be found in Heenan et al. (2004, 1995).

2.2 The APSIM model

The Agricultural Production Systems sIMulator APSIM (Holzworth et al, 2014; Keating *et al.*, 2003) was used to simulate observed soil C dynamics in the two treatments (N0 vs N100). The APSIM model is a process-based bio-physical model designed to study productivity, nutrient cycling and environmental impacts of farming systems as influenced by climate variability and management interventions. The ability of APSIM to simulate soil C and soil nitrogen (N) dynamics has been verified under various cropping systems and agricultural management (Luo *et al.*, 2011, Probert *et al.*, 1998). The model divides soil C into six pools and simulates each pool as a first-order process with the rate constants being modified by factors involving soil temperature, moisture and nutrient availability in the soil layer, which is similar to other widely used soil C models such as Century (Parton *et al.*, 1987) and RothC (Jenkinson, 1990). A detailed conceptual diagram of the model for simulating soil C dynamics is presented by Probert *et al.* (1998) and Luo *et al.* (2014).

APSIM runs on a daily time-step and needs daily weather data as inputs, including radiation, maximum and minimum temperatures, and rainfall. Other required soil parameters includes soil C content, C to N ratio of the bulk soil, soil bulk density, hydraulic parameters, initial soil water and nutrient conditions (NO_3^- and NH_4^+) in each soil layer. All these data and the relevant model initialisation and parameterisation processes were adopted from two former APSIM simulation studies using the same dataset by Luo et al. (2014, 2011).

2.3 Constraining the APSIM model

The model was constrained with observed soil C data from the N0 and N100 treatments. Model parameters were derived through constraining model simulations against observed data from both treatments. Two parameters were targeted: the potential decomposition rate of humic C pool (*rdhum*) and the amount of recalcitrant C pool in total soil C (*finert*). The two parameters directly control the turnover time and decomposability of soil C. Sensitivity analysis of eight main parameters that directly link to C decomposition has indicated that these two parameters were the two most important parameters to which soil C dynamics are most sensitive in the APSIM model (Luo et al., 2015).

Three optimisation strategies were used to optimise the model by minimising the combined rooted mean of squared errors (RMSE, i.e., the objective function for *optimise* and *DEoptim*, see below) between simulated and observed soil C under the two treatments. That is, 1) optimise *finert* only (Opt1), 2) optimise *rdhum* only (Opt2), and 3) optimise *rdhum* and *finert* synchronously (Opt3). We used the similar Bayesian approach of Yeluripati et al. (2009) to derive the posterior distributions of the two parameters (*finert* and/or *rdhum*). Both parameters were bounded within a range that is biologically and physically possible, therefore eliminating solutions in conflict with prior knowledge. For *rdhum*, we assumed that $0.000015 \text{ day}^{-1} \leq \text{rdhum} \leq 0.0015 \text{ day}^{-1}$ (equivalent to around 2–200 years representing an

approximate range of turnover time of humic organic C) and was uniformly distributed, representing our prior knowledge. For *finert*, however, we treated the smallest SOC value (*minC*) in the combined dataset under N0 and N100 as the upper limit of *finert* (because the two treatments originated from the same plot and potentially have similar amount of inert C). Thus, prior distribution of *finert* was a uniform distribution ranging from 0 to *minC*. For Opt1 and Opt2, the function *optimise* for single parameter optimisation in the package *stats* of the scientific computing software R (R Core Team, 2012) was used to find the suitable parameter value. For Opt3, differential evolution algorithm was conducted to optimise *rdhum* and *finert* simultaneously using *DEoptim* function in the package *DEoptim* of R (Mullen *et al.*, 2009).

*Scenario1 – optimising the model using observed average soil C: For model optimisation, a common practice is that model parameters are derived by comparing simulated soil C with the average of measured soil C (based on different replicates) at given time. We treated this practice as the “business-as-usual” scenario, and the replicates for each of the 20 sets of observations under each treatment were used to calculate the average of observed soil C ($\bar{x}$). These averages were used to constrain the model using the three optimisation strategies (Opt1, Opt2 and Opt3). For Opt1 (i.e., optimising *finert* only), *rdhum* was set to the default value (0.00015 day⁻¹) in the model. For Opt2 (i.e., optimising *rdhum* only), the optimised *finert* from Opt1 was used. For Opt1 and Opt2, no uncertainty in the parameters is expected because of the nature of single parameter optimisation. For Opt3 (i.e., optimising *finert* and *rdhum* simultaneously), however, similar model performance can be obtained with a number of ensembles of *rdhum* and *finert*. Using the observed average soil C ($\bar{x}$), 100 ensembles of the two parameters were generated and represented the uncertainty in model parameters. The joint distributions of *rdhum* and *finer* represents the posterior distributions of the parameters inferred by the data. This constraining procedure assumed that $\bar{x}$ represent the true values of soil C stocks (μ), and uncertainty in future simulations with*

these derived parameter sets represents the uncertainty caused by model initialisation and parameterisation.

Scenario 2 – optimising the model considering the uncertainty in soil C observations:

In reality, however, there exists large spatial variability in soil C stock even at the field scale. It is difficult to determine the true probability distribution of soil C and to obtain its statistical characteristics (e.g., mean and variance) using limited replicates. Therefore, estimate of the average (μ^*) has to be combined with distributional assumptions on soil C stocks (such as normality), and the true distribution of soil C stock has to be inferred using statistical characteristics of the samples. Here, a non-parametric bootstrap approach was used to estimate the distribution of μ^* . An estimate of μ^* (i.e., the bootstrap mean) was calculated for the j^{th} observation based on the corresponding observed average ($\bar{x}_j$) and a bootstrap resample of residuals (ϵ_k):

$$\mu_j^* = \frac{\sum_{k=1}^{n_j} (\bar{x}_j \cdot (1 + \epsilon_k))}{n_j}, j = 1, 2, 3, \dots, 20 \quad (1)$$

where $\bar{x}_j$ is the average of the n_j observed replicates for the j^{th} observation, ϵ_k the relative residual for the k^{th} replicate which is randomly sampled from the distribution of relative residuals estimated by pooling together the relative residuals of all observations. For any given set of observation (e.g. j^{th}), the relative residual was calculated as the difference between the replicate and the average of all replicates (for the j^{th} observation) divided by that average. This calculation using Eqn (1) not only ensures that the bootstrap samples are not negative (it is impossible for soil C stock) but also considers the possible soil C change with time. For each of the 20 observations, a total of 100 estimates of μ^* (i.e., 100 sets of data) were obtained (i.e., 100 bootstraps), representing an empirical bootstrap distribution of the “observable” average soil C for a given set of observation. The word “observable” was used

hereafter to indicate that all estimates are possible representation of the true average μ . Model constraining using the three optimisation strategies was performed against each set of the ‘observable’ data to get 100 sets of parameters for the best agreement between simulated and ‘observable’ soil C through minimising RMSE. For the 100 sets of ‘observable’ data, a total of $100 \times 100 = 10,000$ sets of optimised parameter(s) were generated for optimisation strategy Opt3. The 10,000 sets of parameters include the uncertainties induced by model initialisation and parameterisation (as in Scenario 1), as well as those caused by uncertainties in observations.

2.4 Uncertainty in soil C predictions

The constrained model was run from the beginning of the experiment (1979) with the corresponding agricultural management in the two treatments (N0 versus N100), together with either 100 or 100×100 sets of model parameters derived from the two scenarios of model constraining, and continued for a further 100 years (2005–2104). The observed climate data from 1979 to 2013 was used for the corresponding simulation period, and the climate data from 1923 to 2013 was used for the remaining simulation period from 2014 to 2104. Potential future climate change was not considered in this typical study since we focused on uncertainty in soil C predictions induced by uncertainty in observations and model parameterisation.

For each optimisation strategy, the 95% confidence interval (CI, i.e., quantiles corresponding to the probability of 0.025 and 0.975) of projected soil C stock was calculated. The percentage uncertainty (PU) was calculated to indicate the uncertainty of projected soil C under the two scenarios of model constraining:

$$PU = \frac{CI_u - CI_l}{M} \times 100\%, \quad (2)$$

where M is the average of projected soil C stocks considering uncertainties in observations

and/or in model initialisation and parameterisation, CI_l and CI_u are the lower and upper limits of the 95% CI respectively. For Opt1 and Opt2 under scenario 1 (i.e., business-as-usual), uncertainty cannot be estimated because they implicitly assumed that there is no uncertainty in observations and in model initialisation and optimisation.

3 Results

Averaging replicates of each observation, C stock in the top 10 cm soil showed a declining trend in the studied continuous wheat system under both treatments of N0 (no N application) and N100 (100 kg N ha⁻¹ yr⁻¹, Fig. 1). This decline could be well captured by the APSIM model when it was constrained with average values of observational data (Scenario 1) using all three optimisation strategies (i.e., Opt1, Opt2 & Opt3; Fig. 1 and 2). For Opt3, the optimised *finert* and *rdhum* were closely and positively associated (Fig. 2A). Various ensembles of *finert* and *rdhum* could lead to equally well agreement between simulated and observed soil C stocks, but resulted in very divergent soil C predictions, i.e. great prediction

Fig. 1. Simulated and observed soil organic carbon stocks (0–10 cm soil layer) under two treatments of N0 (A, no fertilizer application) and N100 (B, 100 kg N ha⁻¹ yr⁻¹). The model was constrained by observed average soil C stocks (black circles) through optimising *finert* (the amount of inert carbon pool) or *rdhum* (potential decomposition rate of humic organic carbon pool). The simulated soil C stock by separately optimising the two parameters is the same (lines are coincided). Grey circles show the observed replicates.

232 uncertainty (Fig. 2B).

233 Results from the bootstrap approach indicated that ‘observable’ averages of the soil C
 234 measurements were subject to great uncertainty (Fig. 3). In 1979 under N0, for example,

Fig. 2. The distribution and relationship of optimised model parameters (A) and the corresponding simulated soil C dynamics under N0 and N100 treatments (B). The model was constrained by the observed average soil C stocks under two treatments through optimising *finert* (the amount of inert carbon pool) and *rdhum* (potential decomposition rate of humic organic carbon pool) simultaneously. The model constraining period is marked as shading area in (B). The red and blue points are the average of observations, corresponding to the black circles in Fig. 1 for N0 and N100, respectively.

Fig. 3. Uncertainty in observed soil C stocks expressed as the ranges of the 100 empirical bootstrap estimates of “observable” average of soil C stocks for each observation time point under N0 (A) and N100 (B). Any value of the 100 estimates at each observation time point could be used to constrain the model. The year corresponding to the x-axis has been jittered by adding a small random number so that the points do not lie on top of each other.

235 “observable” average soil C stock ranged from 17.66 to 20.98 t ha⁻¹ based on estimations of
 236 100 bootstrapping re-samples (Fig. 3A). Under N100, the corresponding range was from
 237 16.54 to 20.46 t ha⁻¹ (Fig. 3B).

238 Constraining the model using the 100 sets of bootstrapped “observable” average soil
 239 C stocks (Scenario 2—considering uncertainty in observations) resulted in a wide range of

Fig. 4. The distributions and relationship of optimised model parameters. The model was constrained by considering the uncertainty in soil carbon observations. (A) and (B) show the distributions of fitted *finert* (the amount of inert carbon pool) and *rdhum* (potential decomposition rate of humic organic carbon pool), respectively, using three optimisation strategies (Opt1, Opt2 and Opt3). (C) shows the relationship between *finert* and *rdhum* (10,000 ensembles) using optimisation strategy Opt3. Opt1, optimise *finert* only; Opt2, optimise *rdhum* only; Opt3, optimise *finert* and *rdhum* simultaneously.

values for the two parameters (*finert* and *rdhum*, Fig. 4) and in soil C simulations (Fig. 5). Fig. 4 shows that the distributions of the two parameters depend on optimisation strategies. Using Opt3, *finert* ranged from 0 to 13.22 t ha⁻¹ with an average of 8.23 t ha⁻¹ (Fig. 4A), *rdhum* ranged from 0.000065 to 0.000658 day⁻¹ with an average of 0.00030 day⁻¹ (Fig. 4B). Both the ranges and averages of *finert* and *rdhum* were markedly wider and higher than that using Opt1 and Opt2. Additionally, the optimised *finert* and *rdhum* were positively correlated (Fig. 4C), similar to that under Scenario 1 (Fig. 2A).

Under Opt3, using optimised parameter ensembles under Scenario 2 (i.e., considering uncertainty in observations. Fig. 4), the predicted soil C stock was comparable to that using optimised parameter ensembles under Scenario 1 (not considering uncertainty in observations, Fig. 5E and F). Additionally, the averages did not show significant difference (< 3 t ha⁻¹ after 100-year simulations) between the two scenarios (Fig. 5E and F).

In general, percentage uncertainty in soil C projections increased with the years of prediction (Fig. 5). Under Scenario 2, the percentage uncertainty reached 128% and 69% under N0 and N100 respectively using Opt1, 51% and 56% respectively using Opt2, after 100-year simulations. Using Opt3, the percentage uncertainty resulting from model initialisation and parameterisation was 122% and 61% under N0 and N100 respectively under Scenario 1. Further considering the uncertainty in measurement data (Scenario 2) did not further increase the percentage uncertainty in SOC projections, with 97% and 57% percentage uncertainty under N0 and N100 respectively (Fig. 5E and F).

4 Discussion

Accurate prediction of soil C dynamics is critical to credibly predict CO₂ emissions from soil and thus future climate change. Using comprehensive datasets and approaches for model constraining, results of this study demonstrated that great uncertainty in soil C predictions

Fig. 5. Uncertainty in soil C predictions using three optimisation strategies (Opt1, Opt2 and Opt3) under two treatments of N0 and N100. The solid blue and red lines show the predicted average soil C stock without (Scenario 1) and with (Scenario 2) consideration of uncertainty in observations, respectively. The grey and blue lines show the bootstrapping simulation results (100 for Opt1 and Opt2, 10000 for Opt3) under scenario 1 and 2, respectively. In (A), (B), (C) and (D), the blue and red lines are partially coincided. The dashed blue and red lines show the corresponding percentage uncertainty, respectively. Opt1, optimise *finert* (the amount of inert carbon pool) only; Opt2, optimise *rdhum* (potential decomposition rate of humic organic carbon pool) only; Opt3, optimise *finert* and *rdhum* simultaneously.

264 using process-based soil C models could be induced by uncertainties in observations and
 265 model parameterisation. If uncertainties in model initialisation/parameterisation were not
 266 explicitly considered (Fig. 5 A, B, C and D), traditional model constraining based on
 267 measured average soil C trend could mask uncertainty in soil C predictions. Constraining the

model using all available measurement data, including the replicates for each measurement, to define a posterior distribution of model parameters enables the quantification of uncertainty in model predictions. The optimisation procedure like that presented in this study can be incorporated into model and/or software development to facilitate explicit estimate of uncertainties in predictions.

Significant variation in soil C measurement data from the same field forms an additional cause of prediction uncertainty, due to the uncertainty created in model constraining process, which has been ignored in current soil C modelling in the literature. This additional uncertainty source and its impact on simulation results may vary with agricultural management and the level of soil C stock in fields. Although the uncertainties were only quantified in a cultivated soil under the studied continuous wheat system in our study, it is expected to be existent or even amplified in other ecosystems because soil C stock in cultivated soils is relatively homogeneous, comparing with undisturbed soils such as forest soil (Conant *et al.*, 2003, Schöning *et al.*, 2006). In this study, however, we did not assess the potential effect of data quantity and quality on uncertainty in model predictions. More studies on how sampling intensity and experimental duration impact the optimisation of model parameters and prediction uncertainty are required. Then, experimental design and sampling strategy can be developed to minimize uncertainty in model predictions resulting from input data for model constraining. In addition, our study focused on soil C dynamics in the top 10 cm soil. By considering the different environmental conditions in deep and shallow soil layers (e.g., oxygen availability and fresh C inputs), the pattern of uncertainty in soil C dynamics in deeper layers would be different from that in topsoil layers, which warrants further studies.

It is important to note that the calibrated model parameters showed large uncertainty at our studied typical site (Fig. 2A and 4C). The divergent model parameters finally led to

divergent model predictions. A more constrained space of model parameters will certainly reduce uncertainty in model predictions (Weng & Luo, 2011). However, the reality of derived model parameters is difficult to justify without comprehensive understanding of the underlying processes. In process-based models with involvement of multiple collinear parameters, model parameterisation might suffer from the equifinality problem (Luo *et al.*, 2015, Tang & Zhuang, 2008), i.e., different combinations of model parameters enable the model to equally well simulate observations. In this study, for example, inert C pool (*finert*) and potential decomposition rate of humic C pool (*rdhum*) were positively correlated (Fig. 2A and 4C), implying that the equifinality problem also exists in the APSIM model. A realistic representation of the interactions and/or feedback between different C pools and their responses to environmental conditions will be critical for robust model predictions. In addition, however, we acknowledge that this study only focused on two parameters relating to potential decomposition rate and C pool composition. Essentially, soil C dynamics is mediated by microbial processes. Microbial C use efficiency and microbe-mediated pool transformations may change the picture of the estimated uncertainty in soil C predictions.

If uncertainty in model initialisation and parameterisation had been considered, the results suggested that uncertainty in observations did not markedly increase uncertainty in predictions (the range of soil C predictions showed in Fig. 5E and F). These results imply that improvements in data availability (during a specific period of observations) for model constraining may not make up the uncertainty resulting from model structure, supporting the suggestion of that the majority of uncertainty in soil C predictions using process-based model was associated with model structure (He *et al.*, 2014, Ogle *et al.*, 2010). To reduce uncertainty, model structure has to be improved. For example, most of soil C models treat SOM as several conceptual pools and simulate them as a first-order decay process (Smith *et al.*, 1997). This framework should be improved to more explicitly address the heterogeneity

of soil C composition and their interactions with microbial processes (Schmidt *et al.*, 2011, Sierra *et al.*, 2011). These improvements will benefit reducing uncertainty in model parameters and thus in model predictions.

Our simulations demonstrated the importance of considering observation-induced and model parameterisation-induced uncertainties and [their](#) impacts on predicted soil C dynamics. Although our study only assessed the uncertainty using a specific dataset and the specific APSIM model, the model shares the same framework for simulating soil C decomposition processes as other soil C and Earth system models (Friedlingstein *et al.*, 2006, Smith *et al.*, 1997). The results suggest that uncertainties in model-based soil C predictions may be masked because of ignoring observation-induced [uncertainties](#) in the relevant model applications, if [uncertainties](#) in model parameterisation is not explicitly quantified. To reduce observation-induced uncertainties, sophisticated experiment design and sampling strategy are required to obtain more accurate observations such as using consistent microplots for sampling, increasing sample size and applying portable methods for faster analysis of samples (Conant *et al.*, 2003, Don *et al.*, 2007). The prior knowledge of the simulated system (e.g., model parameters and [C pool composition](#)) represented by the model defines the behaviour of the model thereby the space of predictions (Weng & Luo, 2011). [To reduce the parameterisation-induced uncertainties, informative prior distribution of model parameters](#) is required to provide predictions with less uncertainty. [However, regardless of data availability and/or model optimisation approaches, the conceptual nature of C models does not change and the equifinality issue may persistent. We need advanced understanding of microbial-substrate relationships by considering their linkages with measurable variables \(e.g., measurable C fractions and microbial functional groups\).](#)

Acknowledgements

Funding was provided by the Department of Agriculture (DoA) and the Grain Research and Development Corporation (GRDC) of Australia. Thanks to Petra Kuhnert and Ryan Farquharson of CSIRO for their helpful comments on an earlier version of the manuscript.

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