Methods for estimating temperature sensitivity of soil organic matter based on incubation data: A comparative evaluation

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Junyi Liang [a, *], Dejun Li [a], Zheng Shi [a], James M. Tiedje [b], Jizhong Zhou [a], Edward A.G. Schuur [c], Konstantinos T. Konstantinidis [d], Yiqi Luo [a]

[a] Department of Microbiology and Plant Biology, University of Oklahoma, Norman, OK 73019, USA
[b] Center for Microbial Ecology, Michigan State University, East Lansing, MI 48824, USA
[c] Department of Biology, University of Florida, Gainesville, FL 32611, USA
[d] School of Civil and Environmental Engineering and School of Biology, Georgia Institute of Technology, Atlanta, GA 30332, USA

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ABSTRACT

Although the temperature sensitivity (Q_{10}) of soil organic matter (SOM) decomposition has been widely studied, the estimate substantially depends on the methods used with specific assumptions. Here we compared several commonly used methods (i.e., one-pool (1P) model, two-discrete-pool (2P) model, three-discrete-pool (3P) model, and time-for-substrate (T4S) Q_{10} method) plus a new and more process-oriented approach for estimating Q_{10} of SOM decomposition from laboratory incubation data to evaluate the influences of the different methods and assumptions on Q_{10} estimation. The process-oriented approach is a three-transfer-pool (3PX) model that resembles the decomposition sub-model commonly used in Earth system models. The temperature sensitivity and other parameters in the models were estimated from the cumulative CO_2 emission using the Bayesian Markov Chain Monte Carlo (MCMC) technique. The estimated Q_{10}s generally increased with the soil recalcitrance, but decreased with the incubation temperature increase. Our results indicated that the 1P model did not adequately simulate the dynamics of SOM decomposition and thus was not adequate for the Q_{10} estimation. All the multi-pool models fitted the soil incubation data well. The Akaike information criterion (AIC) analysis suggested that the 2P model is the most parsimonious. As the incubation progressed, Q_{10} estimated by the 3PX model was smaller than those by the 2P and 3P models because the continuous C transfers from the slow and passive pools to the active pool were included in the 3PX model. Although the T4S method could estimate the Q_{10} of labile carbon appropriately, our analyses showed that it overestimated that of recalcitrant SOM. The similar structure of 3PX model with the decomposition sub-model of Earth system models provides a possible approach, via the data assimilation techniques, to incorporate results from numerous incubation experiments into Earth system models.

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1. Introduction

Soil organic matter (SOM) is the largest carbon (C) pool in terrestrial ecosystems (Schlesinger, 1995). As a biochemical process, the decomposition of SOM is sensitive to increased temperature (Luo et al., 2001; Fang et al., 2005; Davidson and Janssens, 2006), and consequently has critical impacts on global C cycle and climate change (Cox et al., 2000; Schlesinger and Andrews, 2000). However, SOM consists of many components with different kinetic properties (Davidson and Janssens, 2006), leading to large uncertainty in predicted soil C storage under future climate change (Friedlingstein et al., 2006). Therefore, there is an increasing concern on how temperature sensitivity (expressed as Q_{10}, which measures the change in decay rates for a 10 K warming) depends on the SOM compounds and C qualities (Fang et al., 2005; Conant et al., 2008; Xu et al., 2012). However, the Q_{10} estimation substantially relies on the methods used, which usually have their respective assumptions, leading to contradictory conclusions (Liski et al., 1999; Fang et al., 2005; Rey and Jarvis, 2006; Conant et al., 2008). To better understand the warming impacts on SOM decomposition, it is important to evaluate these methods and the underlying assumptions.

The direct calculation at specific incubation time has been used to estimate the Q_{10} of SOM decomposition based on incubation data

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* Corresponding author. Department of Microbiology and Plant Biology, University of Oklahoma, 101 David L. Boren Blvd., Norman, OK 73019, USA. Tel.: +1 405 325 6519.
   E-mail address: jliang@ou.edu (J. Liang).

using an equation $\left(\frac{R_2}{R_1}\right)^{\frac{10}{T_2-T_1}}$, where T_1 and T_2 are the incubation temperatures, and R_1 and R_2 are the CO_2 emission rates at T_1 and T_2, respectively (Rey and Jarvis, 2006). The estimate is usually an apparent Q_{10} and likely underestimates the temperature sensitivity after the initial incubation stage because greater decomposition results in less substrate at high than low temperatures at the same point of incubation time. To resolve this issue, a method that estimates the apparent Q_{10} by comparing the times for respiring a given amount of C at different temperatures (called the time-for-substrate Q_{10}) has been developed (Rey and Jarvis, 2006; Conant et al., 2008). One important assumption of this method is that a given amount of respired CO_2 is from similar fractions of SOM when the substrates are at the same level at different temperatures (Conant et al., 2008).

In addition, first-order kinetic models have also been used to estimate the Q_{10} (Kätterer et al., 1998; Rey and Jarvis, 2006). In these models, the soil is usually treated as one or several discrete fractions (or pools) based on the turnover times (Kätterer et al., 1998; Rey and Jarvis, 2006). Through these models, the intrinsic Q_{10} (defined as the temperature sensitivity of individual C pools with similar turnover time) for each pool can be derived (Rey and Jarvis, 2006). Generally, the multi-pool models fit the incubation data very well (Kätterer et al., 1998; Rey and Jarvis, 2006). However, these models do not include C transfers across pools which occur in natural ecosystems (Rovira and Vallejo, 2002; Cheng et al., 2007). On the other hand, although three conceptual pools with C transfers among them have been widely used to describe SOM dynamics in Earth system models (Parton et al., 1987; Jenkinson, 1990; Luo et al., 2003), the three-transfer-pool model has never been used, to our knowledge, to estimate temperature sensitivity of SOM decomposition from soil incubation data. Moreover, although a large amount of experimental studies have been conducted and have improved our understanding of the temperature sensitivity of SOM decomposition, the Q_{10} is usually set to be one single value (usually around 2) in Earth system models. It is imperative to find ways to use results from numerous incubation experiments to improve these models.

In this study, we developed a new three-transfer-pool (3PX) model to resemble the model structure of soil carbon dynamics in Earth system models for estimating Q_{10} of SOM decomposition. Then we compared four widely used methods: one-pool (1P) model (Fig. 1a), two-discrete-pool (2P) model (Fig. 1b), three-discrete-pool (3P) model (Fig. 1c), and time-for-substrate (T4S) (Fig. S1) with the 3PX model (Fig. 1d) for Q_{10} estimation using the same data set from a laboratory soil incubation experiment. Parameters of these models were estimated using the Bayesian Markov Chain Monte

Carlo (MCMC) technique, which has recently been used to improve parameterization of ecological models (Xu et al., 2006; Gaucherel et al., 2008; Luo et al., 2011; Ahrens et al., 2014). In these models, the intrinsic Q_{10} for each pool was estimated directly through fitting the CO_2 emission data and the apparent Q_{10} was calculated from the estimated intrinsic Q_{10}, pool size and decay rate of each pool. The T4S method estimates temperature sensitivity by comparing the times for decomposing a given amount of C at different temperatures (Fig. S1) (Conant et al., 2008; Xu et al., 2010; Haddix et al., 2011).

2. Materials and methods

2.1. Soil incubation data

The data used here were from a published paper by Haddix et al. (2011). The soil incubation data collected from a native grassland in Indian Head, Saskatchewan, Canada (50.533 °N, 103.517 °W). The mean annual temperature and precipitation are 2 °C and 421 mm, respectively. Information about soil sampling and incubation was described in detail in Haddix et al. (2011). Briefly, samples were collected from three separated locations that were several meters apart (field replicate $n = 3$). Surface litter and aboveground vegetation were cleared away before sampling and soil from 0 to 20 cm was collected. In the laboratory, rocks, surface litter and root materials were removed. The soil was homogenized and passed a 2-mm sieve before incubation. Then the soil samples were incubated at 15, 25, and 35 °C for 588 days (laboratory replicate $n = 4$). CO_2 emission rates were measured daily during the first 2 weeks of incubation, weekly for the next 2 weeks, and every 4 weeks thereafter. Overall, there were 36 sampling times over the 588-day incubation period. Data at all the 15, 25 and 35 °C were used in this study to evaluate various methods as described below.

2.2. Model description

2.2.1. First-order discrete-pool models
Generally, first-order discrete-pool models have similar structure described in Eq. (1) (Stanford and Smith, 1972; Andrén and Paustian, 1987; Kätterer et al., 1998; Rey and Jarvis, 2006; Li et al., 2013; Schädel et al., 2013):

$$C_{cum} = \sum_{i=1}^{n} f_i C_{tot} \left(1 - e^{-k_i t}\right) \tag{1}$$

where C_{cum} is the cumulative CO_2–C emission at time t (mg C g^{-1} soil), C_{tot} is the initial soil C content (mg C g^{-1} soil), f_i and k_i are the initial fraction and decay rate of the ith pool. The sum of f_is is 1. The only difference of these models is the number of pools (Fig. 1a–c). It is generally assumed that the initial fractions of pools are not affected by incubation temperature (Rey and Jarvis, 2006). Hence, we fitted each of the models with the data at all the three temperatures simultaneously using the data assimilation method described below, and the f_is were set to be independent of incubation temperature.

2.2.2. First-order three-transfer-pool (3PX) model
In addition to the discrete-pool models described above, a three-pool model with transfers among soil pools was developed. The basic concept was derived from the CENTURY and TECO model (Parton et al., 1987; Luo et al., 2003). In the model, SOM dynamics are represented by the following first-order differential equation:
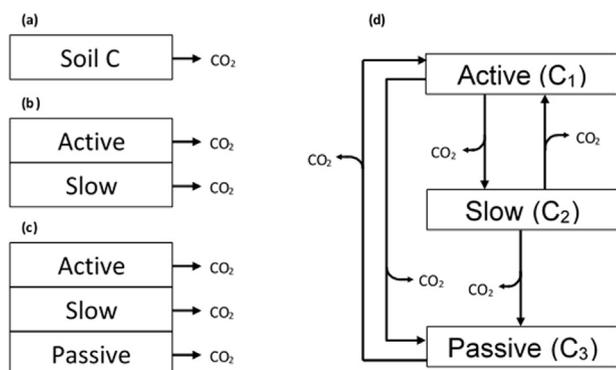
Fig. 1. Model structures of one-pool (a), two-discrete-pool (b), three-discrete-pool (c), and three-transfer-pool (d) models.

$$\frac{dC(t)}{dt} = AKC(t) \tag{2}$$

where A and K are matrices given by

$$A = \begin{pmatrix} -1 & f_{1,2} & f_{1,3} \\ f_{2,1} & -1 & 0 \\ f_{3,1} & f_{3,2} & -1 \end{pmatrix}$$

$$K = \mathrm{diag}(k) = \begin{pmatrix} k_1 & 0 & 0 \\ 0 & k_2 & 0 \\ 0 & 0 & k_3 \end{pmatrix}$$

and $C(t) = (C_1(t) \cdot C_2(t) \cdot C_3(t))^T$ is a 3×1 vector describing soil C pool sizes (Fig. 1d).

Matrix A is C transfers between individual C pools as described by the arrows in Fig. 1d. The elements ($f_{i,j}$) are C transfer coefficients, representing the fractions of the C entering the ith (row) pool from the jth (column) pool. K is a 3×3 diagonal matrix representing decay rates (the amounts of C per unit mass leaving each of the pools per day). As in the above models, those parameters in the 3PX model were also estimated using the data assimilation approach below.

2.3. Data assimilation

We used probabilistic inversion approach described in Xu et al. (2006) and Weng and Luo (2011) to estimate parameters in those models from the soil incubation data. The approach is based on Bayes' theorem:

$$P(\theta|Z) \propto P(Z|\theta)P(\theta) \tag{3}$$

with which the posterior probability density function (PDF) $P(\theta|Z)$ of model parameters (θ) can be obtained from the prior knowledge of parameters represented by a prior PDF $P(\theta)$ and the information in the soil incubation data represented by a likelihood function $P(Z|\theta)$. The prior PDF were specified as the uniform distributions over specific parameter ranges. The likelihood function $P(Z|\theta)$ was calculated with the assumption that errors between observed and modeled values were independent from each other and followed a multivariate Gaussian distribution with a zero mean:

$$P(Z|\theta) \propto \exp\left\{ -\sum_{i=1}^{3} \sum_{t \in obs(Z_i)} \frac{[Z_i(t) - X_i(t)]^2}{2\sigma_i^2(t)} \right\} \tag{4}$$

where $Z_i(t)$ and $X_i(t)$ are the observed and modeled cumulative respiration values, and $\sigma_i(t)$ is the standard deviation of measurements.

The probabilistic inversion was carried on using the Metropolis–Hastings (M–H) algorithm, which is a Markov Chain Monte Carlo (MCMC) technique (Metropolis et al., 1953; Hastings, 1970), to construct the posterior PDFs of parameters. Briefly, the M–H algorithm repeats two steps: a proposing step and a moving step (Xu et al., 2006). In the proposing step, a new point θ^{new} is generated based on the previously accepted point θ^{old} with a proposal distribution $P(\theta^{new}|\theta^{old})$:

$$\theta^{new} = \theta^{old} + \frac{d(\theta_{max} - \theta_{min})}{D} \tag{5}$$

where θ_{max} and θ_{min} are the maximum and minimum values in the prior range of the given parameter, d is a random variable between -0.5 and 0.5 with a uniform distribution, and D is used to

control the proposing step size and was set to 10 in the current study. In the moving step, the new point θ^{new} is tested against the Metropolis criterion (Xu et al., 2006) to examine if it should be accepted or rejected. Because the initial accepted samples are in the burn-in period (Gelman and Rubin, 1992), the first half of accepted samples were discarded and only the rest were used to generate posterior PDFs (Figs. S2–S5). The M–H algorithm was formally run 5 replicates and 500,000 times for each replicate for statistical analysis of the parameters.

It is guaranteed for the Markov chain generated by the M–H algorithm to converge to a unique stationary distribution. In the current study, the convergence of the sampling chains was tested by the Gelman–Rubin (G–R) diagnostic method to ensure that the within-run variation (W_i, Eq. (6)) is roughly equal to the between-run variation (B_i, Eq. (7)) (Gelman and Rubin, 1992).

$$W_i = \frac{1}{K} \sum_{k=1}^{K} \sigma_k^2 \tag{6}$$

$$B_i = \frac{N}{K-1} \sum_{k=1}^{K} \left(\overline{p}^{\cdot k} - \overline{p}^{\cdot \cdot} \right)^2 \tag{7}$$

where K is the number of replicates, N is the number of accepted iterations after burn-in period, $\overline{p}^{\cdot k}$ and σ_k are the mean and standard deviation of the specific parameter in the kth replicate, and $\overline{p}^{\cdot \cdot}$ is the mean of the specific parameter over the five replicates. When the Markov chain reaches convergence, the GR_i (Eq. (8)) is equal to one.

$$GR_i = \sqrt{\frac{W_i(N-1)/N + B_i/N}{W_i}} \tag{8}$$

In this study, GRs of all the parameters of all the models were approximately one (Table S1).

2.4. Q_{10} calculations

In this study, we estimated three types of temperature sensitivity (Q_{10}): Q_{10} of bulk soil, intrinsic Q_{10} for each of the SOM pools, and apparent Q_{10} at different times of soil incubation. Bulk soil Q_{10} at 15 °C was estimated by dividing CO_2 emission rate at 25 °C by the rate at 15 °C at the first incubation day with the assumption that soil compounds and microbial community were the same at the two temperatures. Similarly, the bulk soil Q_{10} at 25 °C was estimated by dividing CO_2 emission rate at 35 °C by the rate at 25 °C at the first incubation day.

Intrinsic Q_{10} of the ith pool was estimated using Eq. (9):

$$Q_{10}^i = \left(\frac{k_i(T_2)}{k_i(T_1)} \right)^{\frac{10}{T_2-T_1}} \tag{9}$$

where T_1 and T_2 are the incubation temperatures, $k_i(T_1)$ and $k_i(T_2)$ are the inherent decay rates of the ith pool at the incubation temperatures. In the current study, T_1 and T_2 are 15 and 25 °C for the Q_{10} calculation at 15 °C, and are 25 and 35 °C for the Q_{10} calculation at 25 °C. In other words, the intrinsic Q_{10} was calculated by $k_i(25)/k_i(15)$ and $k_i(35)/k_i(25)$ at 15 and 25 °C, respectively.

Apparent Q_{10} is dependent on the intrinsic Q_{10} and the size of each C pool in the soil. It was calculated using soil CO_2–C emission rate at T_2 divided by that at T_1 at specific substrate levels and fractions of SOM pools:

Table 1
Maximum likelihood estimates (MLEs) of parameters, P values, R^2 values and Akaike information criterion (AIC) values in the one-pool (1P), two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models simulated to the same soil incubation data. Please see Table S2 for the values of transfer coefficients in the 3PX model.

Model	Initial pool size (%)			Decay rate at 25 °C			Q_{10} at 15 °C			Q_{10} at 25 °C			P	R^2	AIC
	Active	Slow	Passive	Active (10^{-3})	Slow (10^{-4})	Passive (10^{-5})	Active	Slow	Passive	Active	Slow	Passive			
1P	–	–	–	0.22	–	–	1.64	–	–	1.43	–	–	<0.001	0.955	−80.1
2P	5.76	–	–	8.68	0.74	–	2.06	4.52	–	1.25	2.11	–	<0.001	0.999	−260.5
3P	4.65	14.53	–	9.75	3.79	1.37	2.12	3.07	3.53	1.22	1.76	2.67	<0.001	0.999	−256.2
3PX	10.65	19.90	–	8.84	2.57	1.38	2.35	3.33	3.62	1.26	2.00	2.87	<0.001	0.999	−241.3

$$Q_{10}^a = \frac{\sum_{i=1}^{n} R_i(T_2)}{\sum_{i=1}^{n} R_i(T_1)} = \frac{\sum_{i=1}^{n} \left[k_i(T_2) \times C_i \times f_{c,i} \right]}{\sum_{i=1}^{n} \left[k_i(T_1) \times C_i \times f_{c,i} \right]} \quad (10)$$

where k_i is the inherent decay rate of the ith pool at T_1 and T_2, C_i is the C content (pool size) of the ith pool, $f_{c,i}$ is the transfer coefficient from the ith pool to CO_2. $f_{c,i}$ is 1 in the discrete-pool models (i.e., all C comes from the ith pool becomes CO_2 as assumed), and is the difference between 1 and transfer coefficents from ith pool to the other two pools in the 3PX model (e.g., $f_{c,1} = 1 - f_{2,1} - f_{3,1}$). T_1 and T_2 are 15 and 25 °C for the Q_{10} calculation at 15 °C, and are 25 and 35 °C for the Q_{10} calculation at 25 °C.

Besides, T4S Q_{10} is comparing the times for decomposing a given amount of soil C at different temperatures (Conant et al. 2008; Fig. S1):

$$Q_{10} = t_{T_1}/t_{T_2} \quad (11)$$

where t_{T1} and t_{T2} are the times required at T_1 and T_2, respectively. The Q_{10} values for labile and recalcitrant SOM were determined using times taken to respire the first and last 0.5% of initial soil C,

respectively. T_1 and T_2 are 15 and 25 °C for the Q_{10} calculation at 15 °C, and are 25 and 35 °C for the Q_{10} calculation at 25 °C.

2.5. Akaike information criterion (AIC)

The goodness of fit relative to the number of model parameters was evaluated by AIC (Akaike, 1974; Burnham and Anderson, 2004):

$$AIC = a \ln\left(\frac{\sum (\widehat{\varepsilon}_i)^2}{n} \right) + 2b \quad (12)$$

where a is the number of data points, $\widehat{\varepsilon}_i$ is the estimated residual of each data point, and b is the total number of estimated model parameters. The model with a smaller AIC value is more parsimonious (Saffron et al., 2006).

3. Results

The estimated Q_{10}s from all the methods were greater at 15 °C than that at 25 °C (Table 1). The multi-pool models fitted the incubation data better than the single-pool model (Table 1; Fig. 2).
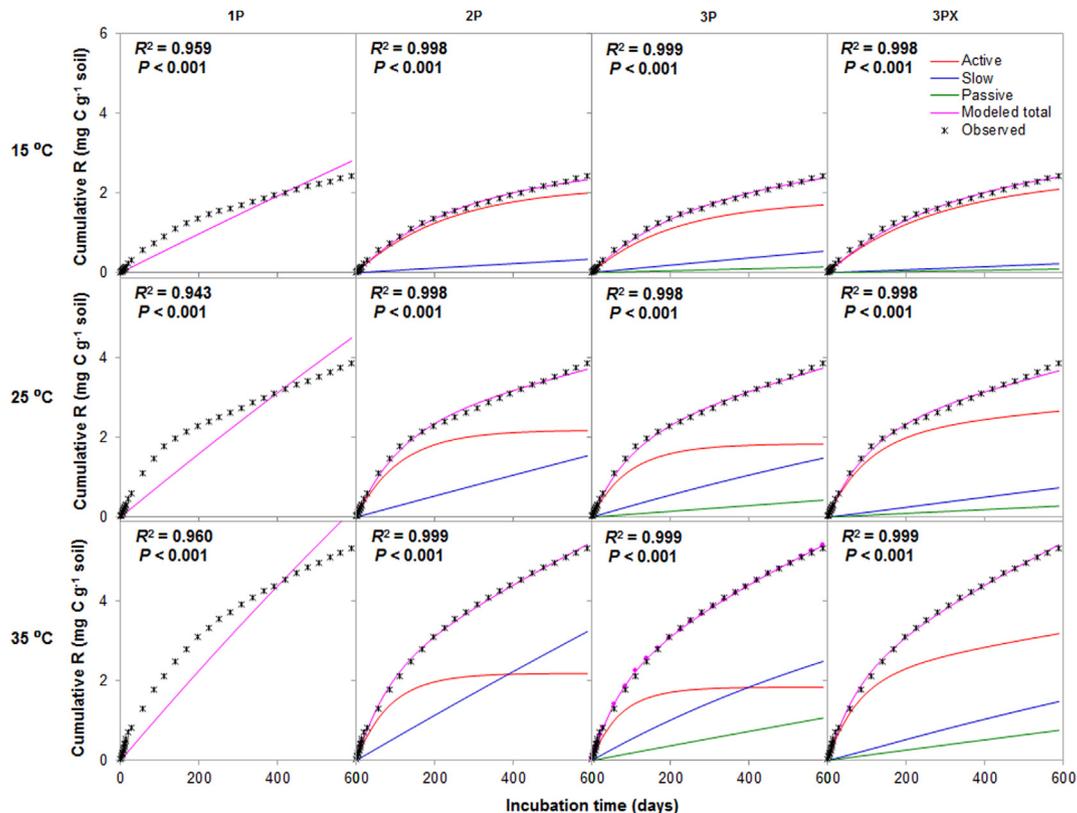
Fig. 2. Observed and modeled cumulative CO_2 releases (R) from individual and total pools at all the three incubation temperatures (i.e., 15, 25, and 35 °C) in the one-pool (1P), two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models.
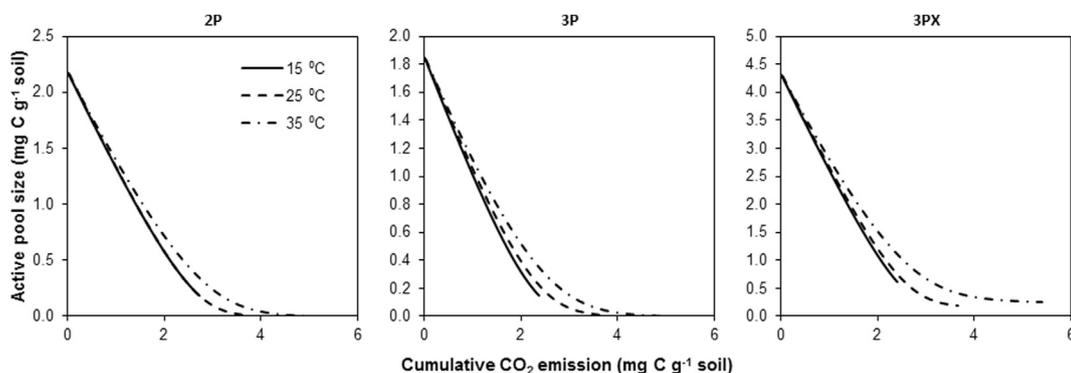
Fig. 3. Simulated dynamics of active pool size against cumulative CO_2 emission at all the three incubation temperatures in the two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models.

Although all the multi-pool models described SOM dynamics adequately, the estimated parameters were different (Table 1, Table S2). The estimated initial active pool size was greater in the 3PX model than that in the 2P and 3P models. Additionally, the decay rate of the slow pool was smaller in the 2P model than those in the 3P and 3PX models. The 1P model can only generate one Q_{10} at each of the temperatures of 15 and 25 °C. In the multi-pool

models, the Q_{10} increased with SOM recalcitrance. Although the fit of all the multi-pool models were highly significant (all $P < 0.001$ and $R^2 > 0.99$), the 2P model had the lowest *AIC* value followed by the 3P model. The *AIC* value of the 3PX was larger than both of these but smaller than that of the 1P model (Table 1).

During the incubation period, the active pool size declined rapidly (Fig. 3). In all the multi-pool models, the remaining active C
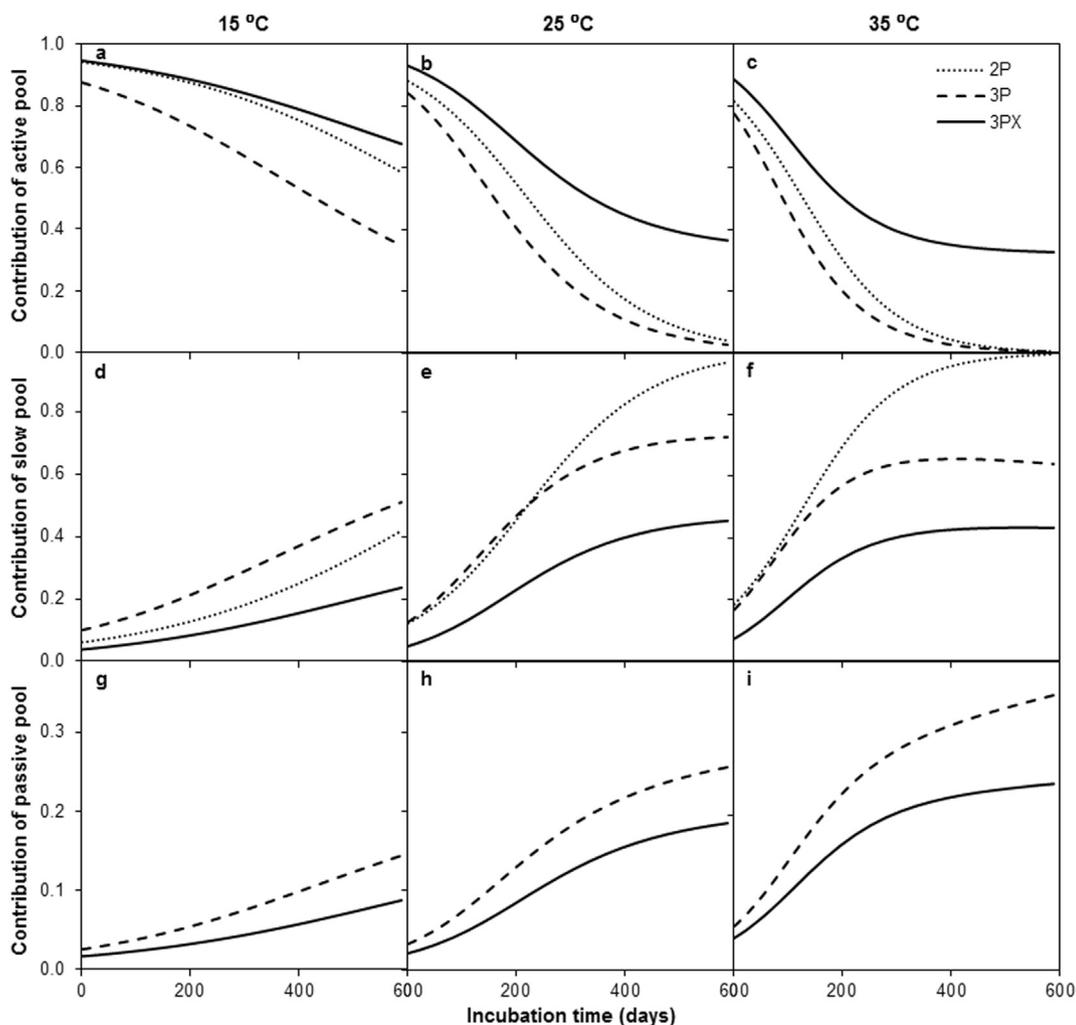
Fig. 4. Simulated contributions of individual pools to CO_2 emission rate at all the three incubation temperatures in the two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models.

was more at higher than that at lower temperatures when the same amount of C was respired, especially in the late incubation period (Fig. 3). In addition, the modeled active pool size was smaller in the 2P and 3P models than that in the 3PX model. In the meantime, the contribution of the active pool to CO_2 emission rate reduced quickly with the incubation progress, while the contributions of the slow and passive pools increased (Fig. 4). The modeled contributions of the active pool to CO_2 emission at all the incubation temperatures were greater in the 3PX model than those in the 2P and 3P models. Correspondingly, the modeled contributions of the slow and passive pools were smaller in the 3PX model over the incubation period (Fig. 4).

Although the temperature sensitivity generally increased with the SOM recalcitrance (Table 1), the estimates were dependent on the methods used (Fig. 5). It seemed that the estimated Q_{10} of bulk soil from all the methods was within the 95% confidence range of the direct calculation at the first incubation day at 15 °C (Fig. 5a), while only the T4S method estimated the Q_{10} of bulk soil at 25 °C appropriately (Fig. 5c). In addition, the difference of the estimated Q_{10}s among these methods changed with the incubation progress (Fig. 5b and d). The only Q_{10} value estimated from the 1P model cannot represent the dynamics of temperature sensitivity with the change in SOM compounds. The discrete-pool models generated higher apparent Q_{10} than the 3PX model at both 15 and 25 °C when the active pool size diminished as the SOM decomposition progressed (Fig. 5b and d). The estimated apparent Q_{10} of the recalcitrant SOM by the T4S calculation was significantly greater than those by all the models at the end of the incubation at 25 °C (Fig. 5d). In addition, the apparent Q_{10} decreased with the increased contribution of the active pool to CO_2 emission rate, and increased with the increase in the contributions of the slow and passive pools to CO_2 emission rate (Fig. 6).

4. Discussion

4.1. Comparison of the models

Generally, the estimated Q_{10} increased with SOM recalcitrance and decreased with the increase in the incubation temperature, which is in accord with the Arrhenius equation and many previous studies (Knorr et al., 2005; Davidson and Janssens, 2006; Conant et al., 2008; Haddix et al., 2011; Xu et al., 2012). However, the estimations substantially rely on the methods used and their respective assumptions. The 1P model assumes the soil as a single C pool (Stanford and Smith, 1972; Kätterer et al., 1998; Rey and Jarvis, 2006). Compared with the multi-pool models, it does not fit the data well enough (Kätterer et al., 1998; Rey and Jarvis, 2006). In addition, it cannot represent the dynamics of temperature sensitivity with the changes in SOM compounds. Therefore, the 1P model is not adequate for describing the dynamics of SOM decomposition in general and estimating the temperature sensitivity in particular. All the 2P, 3P and 3PX models fitted the incubation data adequately ($R^2 > 0.99$, $P < 0.001$), but the modeled decay rates of the slow pool in the 2P model were smaller than those in the 3P and 3PX models. It is mainly because the slow pool in the 2P model conceptually amounts to the sum of slow and passive pools in the three-pool models.

In this study, the Bayesian MCMC technique provided the distributions of estimated parameters for each model (Figs. S2–S5). In the four models, the goodness of the parameter constraint
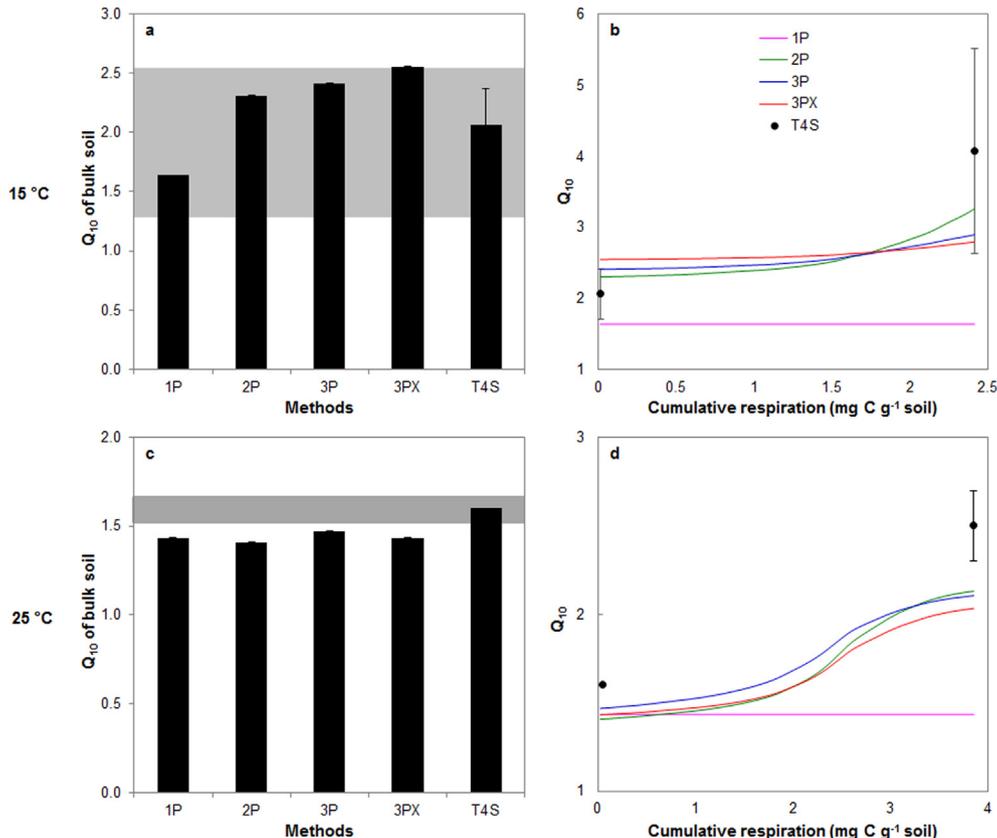
Fig. 5. Estimated Q_{10}s from the one-pool (1P), two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models, and the time-for-substrate calculation (T4S). Panel (a) and (c) show the estimated Q_{10}s of bulk soil from different methods (mean ± 95% CI). The gray areas are the 95% confidence ranges of Q_{10} from direct calculation at the first incubation day at 15 (a) and 25 °C (c), respectively. Panel (b) and (d) show the dynamics of estimated apparent Q_{10}s with SOM respiration.
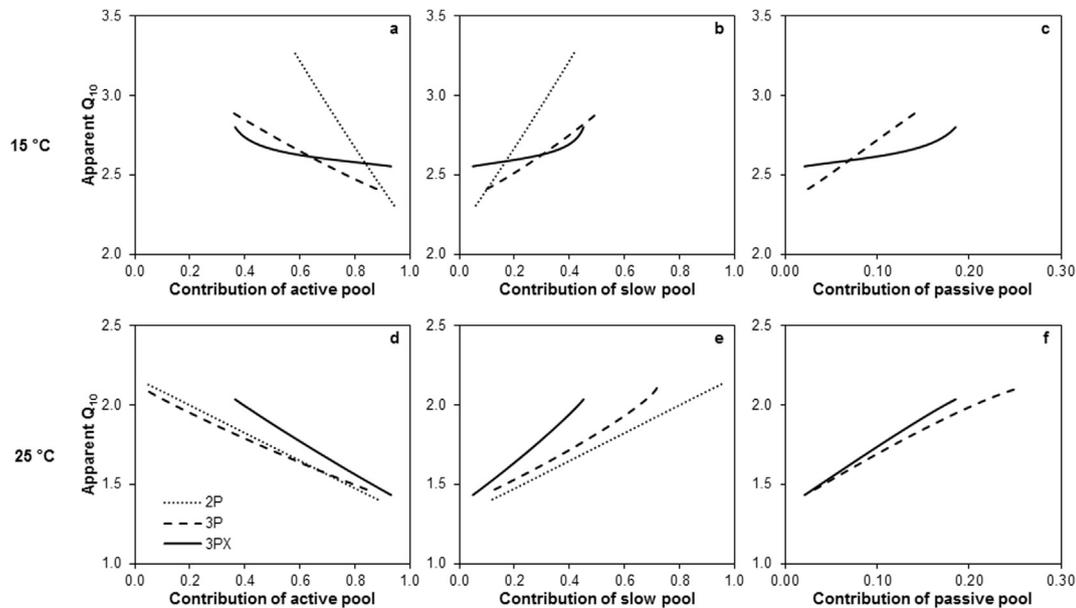
Fig. 6. Relationships of the modeled apparent Q10 and the modeled contributions of the active (a, d), slow (b, e) and passive (c, f) pools to the instantaneous CO_2 emission rate in the two-discrete-pool (2P), three-discrete-pool (3P) and three-transfer-pool (3PX) models.

decreased with the increase in the parameter number. In the 1P model, although the parameters were constrained perfectly, the *AIC* analysis demonstrated that it is the worst model. In the other three models, the *AIC* analysis indicated that the 2P model is the most parsimonious model, followed by the 3P model. The 3PX model seems to have an overfitting issue when it is used to simulate the CO_2—C emission data alone. However, in the 3PX model, the transfers from slow and passive pools can alleviate the rapid consumption of active pool, leading to greater active pool size and its contribution to CO_2 emission rate than that in the discrete-pool models. Because the apparent Q_{10} decreased with the increased contribution of the active SOM to CO_2 emission rate (Fig. 6), the estimated apparent Q_{10}s in the 2P and 3P models were higher than that in the 3PX model after the early incubation period.

4.2. Correlations between parameters

Strong correlations between some parameters were observed in all the four models (Table S3). In these models, the values of *k* at 25 °C and the corresponding Q_{10} at 25 °C of the active pool are usually negatively correlated, meaning when the decay rate at the 25 °C incubation temperature is high, low Q_{10} values are needed to match the data at the 35 °C incubation temperature. In contrast, the values of *k* at 25 °C and the corresponding Q_{10} at 15 °C of the active pool are usually positively correlated, meaning when the decay rate at the 25 °C incubation temperature is high, high Q_{10} values are needed to match the data at the 15 °C incubation temperature. In the multi-pool models, the high initial fraction of the labile pool is accompanied by the low decay rate, mainly because the two parameters are constrained by the information of CO_2 emission from the labile pool synchronously. As a result, there is a trade-off between them. In the 3PX model, the positive correlation between f_1 and $f_{2,1}$ means when more C is allocated to labile pool, more proportion of the labile pool would transfer to the slow pool.

The strong correlations between parameters partly indicate that the models are overparameterized with the available data (Braakhekke et al., 2013). However, the inherent correlations of parameters due to the model structures may be another important reason. For example, the only existed three parameters in the

simplest 1P model are the decay rate (*k*) and Q_{10}s at 15 and 25 °C. The Q_{10}s themselves, measure the responses of the decay rate to temperature. As a result, they are highly correlated with each other (Fig. S3).

4.3. Estimated Q10 from the T4S method

The T4S Q_{10} calculation assumes that the respired CO_2 is from similar SOM fractions at different temperatures at the same substrate levels (Conant et al., 2008). However, the current and many previous studies have indicated that the recalcitrant SOM is more temperature sensitive (Knorr et al., 2005; Craine et al., 2010; Karhu et al., 2010; Xu et al., 2012). As a result, when the same amount of SOM is decomposed, the proportion of emitted CO_2 from the slow and passive pools would be more at high than that at lower temperatures. The results in the current study confirmed that the active pool size increased with the increased incubation temperature when the same amount of CO_2 was respired in all the multi-pool models (Fig. 3). Because the decay rate of the active pool is much greater than that of the slow and passive pools, the CO_2 emission rate at the higher temperatures should be greater than assumed by the method. In other words, the time for respiring a given amount of C was less than assumed. Moreover, the difference between the active pools at different temperatures increased with SOM decomposition (Fig. 3), indicating that the assumption of this method causes little bias for short-term incubation, but it would lead to overestimation of Q_{10} of the recalcitrant SOM decomposition when applying to long-term incubation experiments. This is supported by the results that the estimated Q_{10} of recalcitrant SOM from the T4S method was significantly greater than that from the other methods (Fig. 5d).

4.4. Potential implication of 3PX model

Multi-discrete-pool models assume soil C can be divided into several discrete pools (Andrén and Paustian, 1987; Kätterer et al., 1998; Rey and Jarvis, 2006; Li et al., 2013; Schädel et al., 2013). However, in natural ecosystems there are likely C transfers among soil SOM pools (Rovira and Vallejo, 2002; Cheng et al., 2007) and

the transfers are included in Earth system models (Parton et al., 1987; Jenkinson, 1990; Luo et al., 2003). Although the discrete-pool models can fit the soil incubation data well, the estimated Q_{10} and other parameters with those models could not be directly used to improve Earth system models. The 3PX model, on the other hand, represents different soil pools and transfers among the pools to resemble ecosystem carbon cycle models. Thus, the 3PX model can facilitate knowledge transfer from soil incubation studies to Earth system modeling.

Although the structures of the terrestrial decomposition sub-model may be different in different Earth system models, the 3PX-type model and data assimilation techniques could provide an effective approach to incorporate the incubation data into these large-scale models with minor adjustment of the model structure. For example, the 3PX model in the current study corresponds to the CENTURY and TECO model (Parton et al., 1987; Luo et al., 2003). Instead of the traditional way that giving the parameters specific values, the 3PX model can provide constrained values and the uncertainties from experimental data (Fig. S5). However, because there is little information for the C transfers in the data with CO_2 emission alone, none of the five parameters relative to the C transfers are well constrained. Therefore, data relative to the C transfers should be gathered together with CO_2 emission and used for the estimates of these parameters. For example, isotope measurements have recently been used to constrain the transfer coefficient from the active to slow pool (Ahrens et al., 2014).

4.5. Conclusions

The results in our study indicate that temperature sensitivity estimated from soil incubation data strongly depends on the methods used. The 1P model is not adequate for Q_{10} estimate. The 2P model is the most parsimonious one and can fit data well with all parameters commendably constrained. The 3P model can estimate the C release and its temperature sensitivity of the passive SOM with a minor decrease in the model parsimony. The estimated Q_{10} of the soil with less labile C from the 3PX model is smaller than that from the 2P and 3P models due to considering the transfers among pools. The T4S method is effective to estimate Q_{10} of the labile SOM, but would overestimate that of the recalcitrant SOM. The 3PX model structure offers a possible approach to facilitate the transfer of knowledge learned from soil incubation data into Earth system models.

Acknowledgments

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.soilbio.2014.10.005.

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