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Quantifying the short-term dynamics of soil organic carbon decomposition using a power function model

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Abstract

Introduction: Soil heterotrophic respiration (R_h , an indicator of soil organic carbon decomposition) is an important carbon efflux of terrestrial ecosystems. However, the dynamics of soil R_h and its empirical relations with climatic factors have not been well understood.

Methods: We incubated soils of three subtropical forests at five temperatures (10, 17, 24, 31, and 38 °C) and five moistures (20, 40, 60, 80, and 100% water holding capacity (WHC)) over 90 days. R_h was measured throughout the course of the incubation. Three types of models (log-linear, exponential, and power model) were fitted to the measurements and evaluated based on the coefficient of determination (r^2) and Akaike Information Criterion (AIC) of the model. Further regression analysis was used to derive the empirical relations between model parameters and the two climatic factors.

Results: Among the three models, the power function model ($R_h = R_i t^{-k}$) performed the best in fitting the descending trend of soil R_h with incubation time ($r^2 > 0.69$ for 26 of 30 models). Both R_i and k generally increased linearly with soil temperature but varied quadratically with soil moisture in the three forest soils.

Conclusions: This study demonstrated that the power function model was much more accurate than the exponential decay model in describing the decomposition dynamics of soil organic carbon (SOC) in mineral soils of subtropical forests. The empirical relations and parameter values derived from this incubation study may be incorporated into process-based ecosystem models to simulate R_h responses to climate changes.

Keywords: Soil respiration, Subtropical forest, Moisture, Temperature, Power function, Climate change

Introduction

Soil heterotrophic respiration (R_h) is a major component of soil CO₂ efflux resulting from microbial decomposition of litter and soil organic carbon (SOC) (Luo et al. 2001; Davidson and Janssens 2006; Richardson et al. 2012). Many studies about the environmental controls of R_h have been conducted over the past decades using both field experiments and laboratory incubations (Giardina and Ryan 2000; Fang et al. 2005; Curiel Yuste et al. 2007; Deng et al. 2012). Previous field observations and experiments generally characterized the diurnal, seasonal, or annual variation patterns of soil CO₂ fluxes and derived their empirical relations with environmental

factors such as temperature and moisture (Raich and Schlesinger 1992; Bond-Lamberty and Thomson 2010; Wei et al. 2015). Although field studies have the advantage of investigating soil CO₂ fluxes in less or undisturbed soils, the influential environmental factors are often confounded with each other under field conditions. For instance, the increase of soil temperature may cause the decrease of soil moisture (Kirschbaum 1995; Davidson et al. 1998). Moreover, the temperature and moisture effects may also be confounded by other biotic and abiotic factors such as substrate availability and microbial biomass (Wei et al. 2015). Laboratory incubation experiment was considered the most unbiased method to investigate intrinsic soil R_h variation patterns and underlying mechanisms (Kirschbaum 1995) because it can isolate the effects of a single process on system dynamics, which may be impossible in nature. Many lab

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incubation studies therefore have been conducted to quantify biotic and abiotic effects on soil organic matter (SOM) decomposition (Kirschbaum 1995; Dalias et al. 2001; Iqbal et al. 2009; Curtin et al. 2012). For example, researchers incubated mineral soils under certain temperatures and moistures and measured CO_2 release from the soil (i.e., R_h) at different time intervals over a given period of time (Giardina and Ryan 2000; Fang et al. 2005; Thiessen et al. 2013; Zhou et al. 2014). These data were often used to quantify the dynamics of SOM decomposition and to investigate the temperature sensitivity of soil R_h (Fierer et al. 2005; Craine and Gelderman 2011; Zhou et al. 2014).

Up to date, exponential decay model has been widely used to describe the dynamics of SOM decomposition (Fang et al. 2005; Wu et al. 2006; Ise and Moorcroft 2006; Tan and Chang 2007; Song et al. 2010; Iqbal et al. 2009; Lee et al. 2014) because of its relatively simple form and reasonable goodness of fit especially for the early stage of SOM decay (Gholz et al. 2000). The exponential decay model was first proposed by Jenny et al. (1949) and later developed by Olson (1963) to quantitatively describe the first-order kinetics of SOM decomposition. It is often used for predictive purposes based on the assumption that the decomposition rate is constant and that all material can be decomposed (Berg and McClaugherty 2014). However, Aber et al. (1990) pointed out that predictions of SOM decomposition rates using a certain model are not necessarily universally applicable. Huang and Schoenau (1997) compared linear, second-order kinetics, exponential, logarithmic, and power models in describing the short-term leaf litter decomposition dynamics. Their results showed that the exponential model was not the one with the best fit. Instead, a polynomial second-order model fitted the best for aspen leaves while a logarithmic model fitted the best for hazel and mixed leaves, indicating that different models may be suitable for different kinds of leaf litter differing in quality and quantity.

Process-based ecosystem models have been widely used to simulate ecosystem responses to climate changes, although they often require vast amount of input data for model parameterization (Hui and Luo 2004; Ise and Moorcroft 2006; Shen et al. 2008; Shen et al. 2009; Davidson et al. 2012). While process-based models are considered better at forecasting future changes, empirical models (e.g., exponential decay model) are often used to fitting observational data due to their simple forms and ease of parameter estimation (Olson 1963; Meentemeyer 1978; Zhang et al. 2008; Hui and Jackson 2009; García-Palacios et al. 2013). Furthermore, such simple empirical models (e.g., the Q_{10} function describing the relationship between R_h and temperature) are the key constituents of more sophisticated ecosystem

process models (Shen et al. 2008; Shen et al. 2009). Deriving accurate empirical relations and parameter values for particular ecosystems is therefore an important step for the development and parameterization of ecosystem models (Luo et al. 2001; Hui and Luo 2004; Shen et al. 2008; Shen et al. 2009; Davidson et al. 2012; Bauer et al. 2008). Although the exponential decay model had been used to describe leaf litter decomposition process in plantation forests of southern China (Li et al. 2001), few studies have derived the empirical relations between SOC dynamics and climatic factors for the mineral soils of subtropical forests. This is in spite of the fact that subtropical forests in southern China are the largest carbon sink of the country, and the soils play a critical role in the carbon balance of the region (Piao et al. 2009; Wei et al. 2015).

In this study, we incubated soils from three subtropical forests under a range of temperatures and moistures over 90 days and measured soil R_h during the course of the incubation. The main objectives were (1) to quantify the dynamics of soil R_h for various forest soils under different soil temperature and moisture treatments, (2) to test the suitability of different empirical models (e.g., log-linear, exponential, and power functions) in simulating the short-term dynamics of R_h flux or SOC decomposition, and (3) to derive the empirical relations between model parameters and soil climatic conditions.

Methods

Soil sampling and incubation experimental design

The laboratory incubation experiment was conducted at South China Botanical Garden, Chinese Academy of Sciences (CAS) in Guangzhou, China. Soils were collected at the top soil layer (0–20 cm) from three subtropical forests at the Heshan National Ecosystem Observation and Research Station (22° 34' N, 112° 50' E), about 80 km away from the Guangzhou City. The three forests included a plantation of *Pinus elliottii* (PE), a plantation of *Schima superba* (SS), and a subtropical coniferous and broadleaf mixed forest (CB). Soil total organic carbon content (TOC) were 14.8 (± 0.26), 13.3 (± 0.32), and 16.95 (± 0.46) mg g⁻¹ dry soil; total nitrogen (TN) were 1.05 (± 0.01), 0.99 (± 0.02), and 1.22 (± 0.02) mg g⁻¹ dry soil; total phosphorus (TP) were 0.19 (± 0.008), 0.22 (± 0.005), and 0.25 (± 0.004) mg g⁻¹ dry soil for PE, SS, and CB, respectively. Soil bulk density (BD) were 1.4 g cm⁻³ for PE and SS, and 1.027 g cm⁻³ for CB. Soil pH (KCl extraction) were 3.58 (± 0.08), 3.34 (± 0.02), and 3.32 (± 0.01) for PE, SS, and CB, respectively. The detailed description of soil sample collection, laboratory incubation, and measurements can be found in Zhou et al. (2014). Here, we briefly described the relevant experimental design and measurements.

In each forest, we established four plots ($10 \times 10 \text{ m}^2$) at least 10 m apart from each other to collect replicated soil samples. We randomly located five sampling spots (area = $20 \times 10 \text{ cm}^2$) within each plot and collected five soil samples to the depth of 20 cm. The five random samples were homogenized to form a composite sample for each plot. We therefore had four replicated soil samples for each forest, with each composite sample weighing about 50 kg in fresh weight. All soil samples were transported to the laboratory and sieved through a 2-mm sieve to remove coarse plant and mineral materials.

The laboratory incubation experiment was conducted using a full factorial design with two factors (temperature and moisture) and five treatment levels for each factor. The five temperature levels were 10, 17, 24, 31, and 38°C , and the five moisture treatment levels were 20, 40, 60, 80, and 100% water holding capacity (WHC). The total number of treatments for each forest was 25 (five temperature treatments time five moisture treatments). Each treatment had four replicates from the four composite samples, thus resulting in 300 incubation soil samples in total (25 treatments \times 4 replicates \times 3 forest soils). Each incubation sample weighing $\sim 50 \text{ g}$ of oven-dried soil was added to each Erlenmeyer flask that was covered by rubber stoppers with small holes to reduce evaporative water loss and maintain gas exchange. Soil water content was adjusted to corresponding soil moisture level by adding deionized water using a pipette. Soil temperature was controlled using the thermostat incubator (RXZ-600B, Southeast Instrument Co., Ltd., Ningbo, China). Soil R_h was measured using Li-6262 infrared gas analyzer (Li-Cor Inc., Lincoln, Nebraska, USA) at the days of 1, 2, 3, 4, 6, 7, 13, 18, 27, 34, 41, 53, 62, 74, and 90. It is noted here that the R_h data of SS on day 7, day 30, and day 90 had been reported in Zhou et al. (2014), which were used to assess the moisture effects on the temperature sensitivity of R_h ; here, the data were mainly used to derive empirical relations.

Statistical modeling and analysis

We fitted log-linear, exponential, and power function models to the R_h —incubation time data pairs for all the three forest soils, and then assessed the performance of the three models based on coefficient of determination (r^2) and Akaike Information Criterion (AIC). The r^2 is a measure of goodness of fit of the model while AIC offers a relative estimate of the information lost when a given model is used to represent the process that generates the data. Therefore, larger r^2 values represent a better goodness of fit while lower AIC values indicate a relatively higher quality of the model. The three models are as follows:

$$R_h = a + b \text{Log}(t) \quad (1)$$

$$R_h = a \text{Exp}(bt) \quad (2)$$

$$R_h = at^b \quad (3)$$

where R_h is the soil heterotrophic respiration at time t , a and b are two parameters.

Besides assessing the performance of different models, we tested the differences of the best model parameters among the three forest soils using analysis of variance (ANOVA). All data analyses were performed in SAS 9.3 (SAS Inc., Cary, NC).

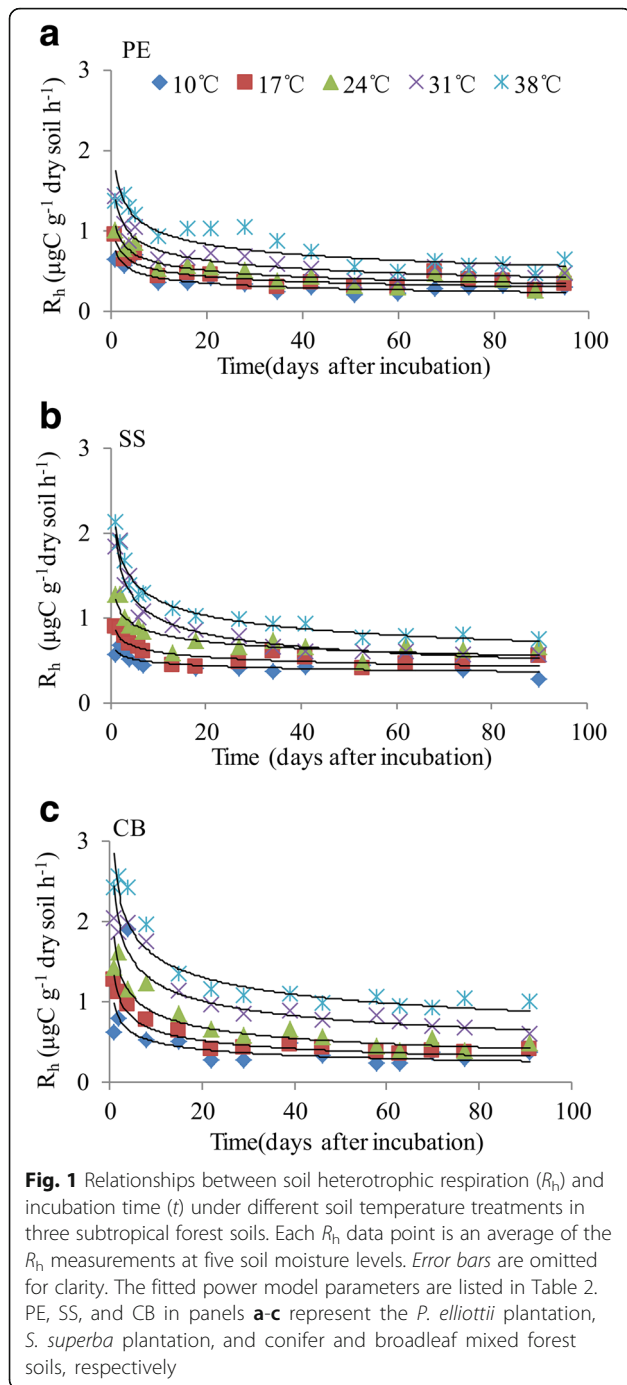
Results

Modeling the dynamics of soil R_h

Under all the temperature and moisture treatments for the three forest soils, soil R_h showed similar dynamic patterns: the highest R_h appeared in the beginning of the incubation and declined rapidly in the first 10–20 days, then leveled off eventually (Figs. 1 and 2). Although all the three models could quantitatively describe the dynamic behavior, the power function model provided the best fit for the measurements, since AIC was the lowest and r^2 the highest for the power function model compared with the other two models (Table 1). This was also consistent across all the three forest soils. For most of the power function models (26 out of 30; 15 for the temperature treatments (Fig. 1) and 15 for the moisture treatments (Fig. 2)), the r^2 values were larger than 0.69 (Table 2). The power function model ($R_h = R_I t^{-k}$, with R_I being the R_h at $t = 1$ and k the power) was therefore used to describe the dynamics of soil R_h for all treatments and forest soils hereafter.

For temperature treatments, soil R_h was higher under higher temperatures, particularly in the beginning of the incubation (Fig. 1). Soil R_h was the largest under the 38°C treatment and the lowest under the 10°C treatment. Among the three forest soils, PE soil had the lowest soil R_h (Fig. 1a) and CB the highest (Fig. 1c). Averaged over the 15 measurement times during the 90-day incubation, soil R_h was 0.577, 0.723 and $0.876 \mu\text{g C g}^{-1} \text{ dry soil h}^{-1}$ for the PE, SS, and CB forests, respectively. The power function model fitted soil R_h dynamics well at all the five temperature levels, with the r^2 ranging from 0.55 to 0.97 (Table 2). The r^2 was lower under 10°C than the other temperature levels, indicating a relatively poor goodness of fit of the model at a low temperature (Table 2). The initial respiration R_I and power k of the model generally increased with temperature.

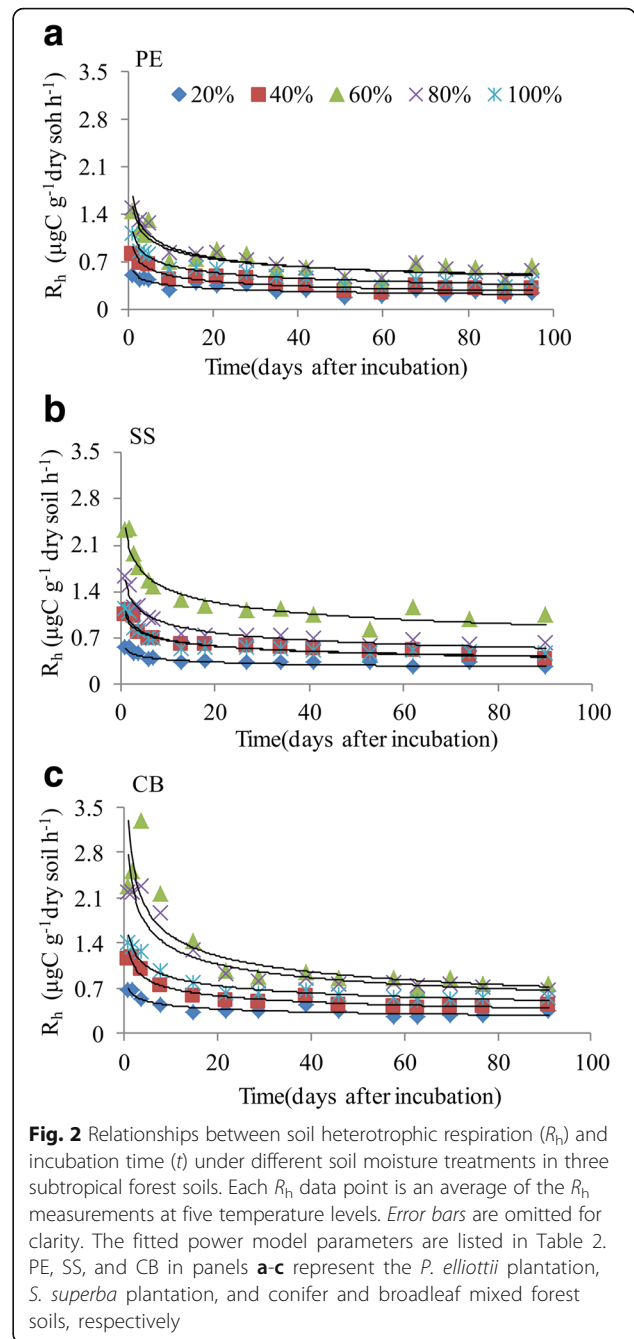
For soil moisture treatments, the largest R_h appeared at the 60% WHC moisture level, followed by the 80% WHC (Fig. 2). Soil R_h was the lowest under the 20% WHC moisture level in all the three forest soils. The r^2 of power function models ranged from 0.69 to 0.92 (Fig. 2 and Table 2) and was lower under the 20% WHC moisture than higher moisture levels, indicating that the power function model received a relatively poorer goodness of fit at a dry



condition. The initial respiration R_1 and power k were generally larger at 40–80% WHC than those at 20 and 100% WHC (Table 2), indicating that R_h declining rate was faster at moderate moisture conditions than at very dry or wet conditions.

Half-life of soil R_h

While the power function model described the declining trend of R_h with incubation time well as shown in Figs. 1 and



2, the half-life of soil R_h reduction (i.e., the time it takes for soil R_h to be reduced to 50% of its starting value) could provide a simple indicator of SOC decomposition rate. The shorter the half-life, the faster the SOC decomposition. Based on the power function, we estimated the half-life of soil R_h ($t_{1/2}$) using the equation $t_{1/2} = \frac{\ln(0.5)}{k} = \frac{\ln(0.5)}{k}$, with k being the component as given in Eq. (3) in the method section.

The estimated $t_{1/2}$ of soil R_h varied from 8.3 to 175.0 days under different soil temperature and moisture

Table 1 Comparison of three statistical models relating heterotrophic soil respiration (R_h) to incubation time (t) in three subtropical forest soils

Model ^a		PE ^b	SS	CB
Log-linear	a, b	1.0290, -0.1250	1.2802, -0.1788	1.8248, -0.3020
$R_h = a + b\text{Log}(t)$	AIC	-57.68	-70.52	-48.08
	r^2	0.51	0.90	0.88
Exponential	a, b	0.4152, -0.0207	0.5894, -0.0173	0.9690, -0.0267
$R_h = a\text{Exp}(bt)$	AIC	-50.94	-50.40	-38.04
	r^2	0.67	0.62	0.71
Power	a, b	0.9754, -0.2355	1.1125, -0.1862	2.4384, -0.2782
$R_h = at^b$	AIC	-61.27	-75.14	-54.28
	r^2	0.82	0.93	0.91

^aIn deriving the empirical models, one R_h data point at each measurement day was the average of the R_h measurements under the 25 experimental treatments (i.e., 5 temperatures \times 5 moistures)

^bPE, SS, and CB represent the *P. elliotii* plantation, *S. superba* plantation, and conifer and broadleaf mixed forest soils, respectively

treatments, but most of them were less than 20 days (Table 3). We could clearly see that the half-life of R_h was much longer under the lowest temperature (10 °C) and the driest moisture (20% WHC) conditions (Table 3), indicating a slower SOM decomposition under cool and dry conditions. Forest soil type also had significant effects on $t_{1/2}$ under different temperature ($P = 0.03$) and moisture ($P = 0.04$) treatments. The SS soil had the longest half-life of R_h , followed by the PE and CB soils (Table 3), indicating that the SOM decomposition rate was slower in SS soils compared with the other two soils.

Table 2 Parameters and coefficient of determination (r^2) of the power function model fitting the change of soil heterotrophic respiration (R_h) with incubation time in three subtropical forest soils

	Initial R_h (R_1) ^b	PE ^a			SS			CB		
		Power (k) ^b	r^2		Initial R_h (R_1)	Power (k)	r^2	Initial R_h (R_1)	Power (k)	r^2
Temperature (°C)										
10	0.628	0.236	0.720	0.582	0.136	0.612	0.747	0.268	0.555	
17	0.768	0.243	0.793	0.702	0.134	0.581	1.137	0.307	0.946	
24	0.944	0.238	0.760	0.998	0.167	0.764	1.456	0.293	0.905	
31	1.276	0.253	0.855	1.647	0.266	0.963	2.054	0.268	0.942	
38	1.712	0.252	0.821	1.913	0.232	0.965	2.523	0.242	0.937	
Moisture (% water holding capacity)										
20%	0.494	0.195	0.692	0.514	0.159	0.874	0.576	0.201	0.708	
40%	0.847	0.270	0.858	1.038	0.206	0.913	1.179	0.278	0.917	
60%	1.423	0.232	0.739	2.118	0.202	0.901	2.928	0.328	0.863	
80%	1.578	0.266	0.893	1.262	0.201	0.891	2.364	0.314	0.922	
100%	1.059	0.259	0.917	0.913	0.180	0.861	1.362	0.255	0.909	

^aPE, SS, and CB represent the *P. elliotii* plantation, *S. superba* plantation, and conifer and broadleaf mixed forest soils, respectively

^bTo derive the empirical relation for each temperature level, R_h under the five moisture levels were averaged; to derive that for each moisture level, R_h under the five temperature levels were averaged. All models are significant at $\alpha = 0.05$

Influence of soil temperature and moisture on model parameters

The ANOVA analysis showed that there were clear differences in model parameters (k and R_1) among the three forest soils (Figs. 3 and 4). Under temperature treatments, forest soil type effect on initial respiration R_1 was not significant ($P = 0.37$). k value was significantly influenced by forest soil type ($P = 0.009$), being significant lower in the SS soil (0.187) than in the CB (0.276) and PE (0.244) soils. Under moisture treatments, forest soil type effect on R_1 was also not significant ($P = 0.36$), but its effects on k were also significant ($P = 0.014$). The k value was significantly lower in the SS soil (0.190) than in the CB (0.275) and PE (0.244) soils ($P = 0.007$).

The values of k and R_1 were also markedly affected by soil temperature and moisture. In all forest soils, R_1 increased linearly with the increase of soil temperature (Fig. 3). The value of k also increased linearly with soil temperature in the PE and SS soils, reflecting a faster declining rate of R_h under warmer temperatures for these two soils. However, k showed a quadratic response to temperature in the CB soil (Fig. 3c), indicating the optimum temperature range for soil R_h in this forest soil was narrower relative to those for the PE and SS soils. With respect to the soil moisture treatments, both R_1 and k increased quadratically with moisture to the highest values at around 60% WHC and declined at lower and higher soil moistures (Fig. 4).

Discussion

Like plant litter decomposition, SOC decomposition is a complex process involving several key components such as

Table 3 Half-life ($t_{1/2}$) of soil heterotrophic respiration (R_h) for three subtropical forest soils incubated over 90 days under five temperature and five moisture levels

	PE ^a		SS		CB	
	Half-life ($t_{1/2}$)	$R_h(t_{1/2})$	Half-life($t_{1/2}$)	$R_h(t_{1/2})$	Half-life ($t_{1/2}$)	$R_h(t_{1/2})$
Temperature (°C)						
10	18.8	0.314	161.4	0.291	13.3	0.374
17	17.3	0.384	175.0	0.351	9.6	0.569
24	18.4	0.472	63.8	0.499	10.6	0.728
31	15.5	0.638	13.5	0.823	13.3	1.027
38	15.7	0.856	19.9	0.956	17.5	1.261
Moisture (% water holding capacity)						
20%	34.8	0.247	79.3	0.257	31.3	0.288
40%	13.0	0.423	29.1	0.519	12.1	0.590
60%	19.9	0.712	31.1	1.059	8.3	1.464
80%	13.6	0.789	31.4	0.631	9.1	1.182
100%	14.6	0.529	46.9	0.457	15.1	0.681

^aPE, SS, and CB represent the *P. elliotii* plantation, *S. superba* plantation, and conifer and broadleaf mixed forest soils, respectively

microorganisms, quantity and quality of SOC substrates, and environmental factors (Fang et al. 2005; Davidson and Janssens 2006; Zhou et al. 2014). Exponential decay model has been widely used to describe the dynamics of SOM decomposition (Paul et al. 1999; Iqbal et al. 2009), but few previous studies have tested the generality of its use in comparison with the other models. No fully controlled incubation experiments, to our knowledge, have been devoted to deriving the empirical relations between soil R_h and climatic factors for subtropical forest soils of southern China. We used soil R_h as a proxy of SOC decomposition in this study and demonstrated that the power function model was more accurate than the widely used exponential decay model in fitting the short-term dynamics of SOC decomposition in three subtropical forest soils.

To compare the dynamic behaviors between a power function model and an exponential model, we plotted the fitting curves of the two models in Fig. 5 using the parameters ($a = 2.4384$ and $b = -0.2782$) listed in Table 2 for the CB forest soil. The descending trend was much faster for the exponential model than that for the power function model, especially at the early stage of SOC decomposition (<13 days of incubation). We therefore argue that exponential decay models may be more suitable for describing the decomposition process of labile organic carbons (e.g., leaf litter or glucose amended in mineral soils) as have been frequently reported in literature (Blagodatskaya et al. 2009; Nottingham et al. 2009; Berg and McClaugherty 2014), whereas power function models may be more suitable for recalcitrant organic carbons require a slower decomposition process. In many process-based ecosystem models such as CENTURY (Parton et al. 1988; Paustian et al. 1992) and PALS (Reynolds et al. 2000; Shen et al. 2009), both the labile and

recalcitrant SOC pool dynamics were described using exponential decay models. Based on the results of this incubation experiment and the modeling analysis, we suggest that power function models should be used to describe the dynamics of recalcitrant carbon pools.

Moreover, power function models are equally good as exponential models for that the two key model parameters (R_1 and k) have clear ecological meanings. When log-transformed, the power function receives the form of $\ln(R_h) = \ln(R_1) - k \ln(t)$. Here, power k is the slope of the log-transformed linear function and therefore indicates the rate of soil R_h change. The initial respiration R_1 means the starting soil R_h at the beginning of incubation when $t = 1$. In all the three forest soils, both k and R_1 varied with temperature and moisture but in different patterns, which may be a reflection of the variations in substrate availability and microbial communities among different soils. It is well known that SOC decomposition is an enzyme-driven, microbe-mediated biological process (Luo et al. 2001; Craine and Gelderman 2011). At higher temperatures (e.g., 31 and 38 °C), microbes are usually more active and grow faster, which explains why R_1 was larger at warmer than lower temperatures (e.g., 10 °C). The faster growth of microbes under warmer temperatures may result in a greater carbon consumption and therefore a shorter half-life ($t_{1/2}$) of R_h (Table 3). This pattern is consistent with what had been found in Nambu et al. (2008) that $t_{1/2}$ was inversely related to R_1 . Similar to R_1 , k was also larger under higher than lower temperatures in SS and PE forests (Fig. 3a, b). The different response patterns of k for the CB soil (Fig. 3c) may be ascribed to the differentiated soil properties between the natural CB forest and the man-made SS and PE plantations.

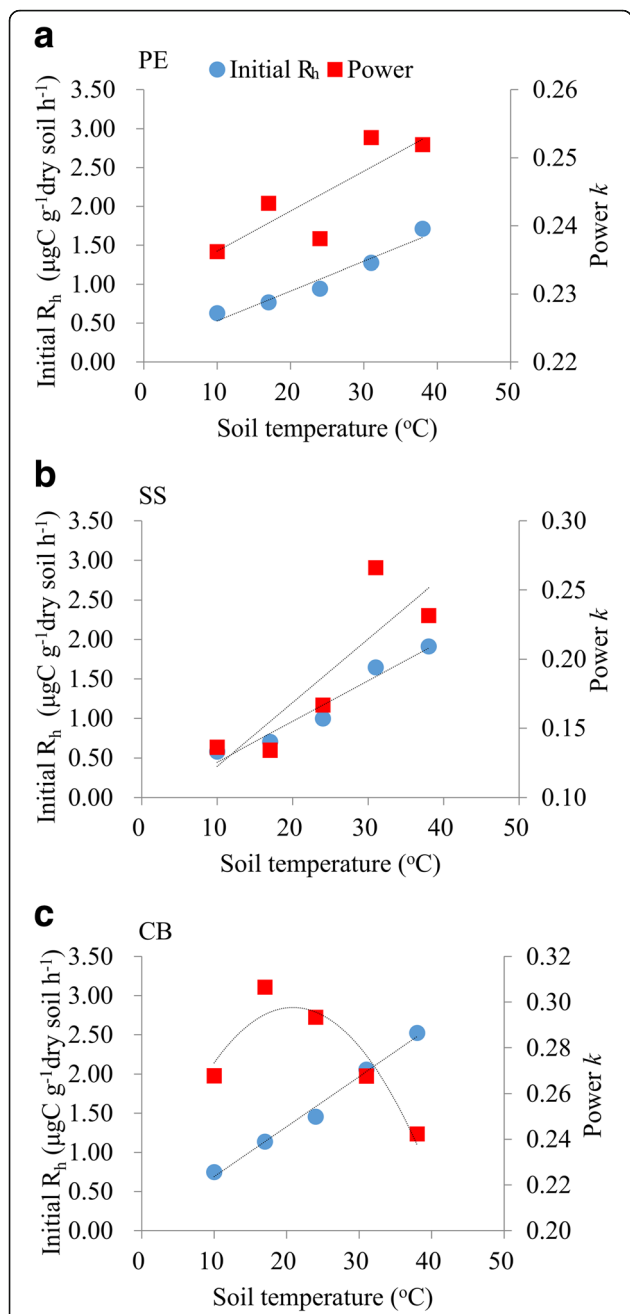


Fig. 3 Empirical relations between the power model parameters (R_1 and k) and soil temperature (T) in three subtropical forest soils. R_1 is the initial respiration, i.e., the starting value of R_h when $t = 1$; k is the power indicates the rate of R_h change. PE, SS, and CB in panels **a-c** represent the *P. elliotii* plantation, *S. superba* plantation, and conifer and broadleaf mixed forest soils, respectively. Models of fitting for PE, $R_1 = 0.001 T + 0.230$ ($r^2 = 0.71$), $k = 0.038 T + 0.148$ ($r^2 = 0.94$); for SS, $R_1 = 0.052 T - 0.068$ ($r^2 = 0.95$), $k = 0.046 T + 0.076$ ($r^2 = 0.74$); for CB, $R_1 = 0.064 T + 0.052$ ($r^2 = 0.99$), $k = -0.0002 T^2 + 0.009 T + 0.208$ ($r^2 = 0.89$)

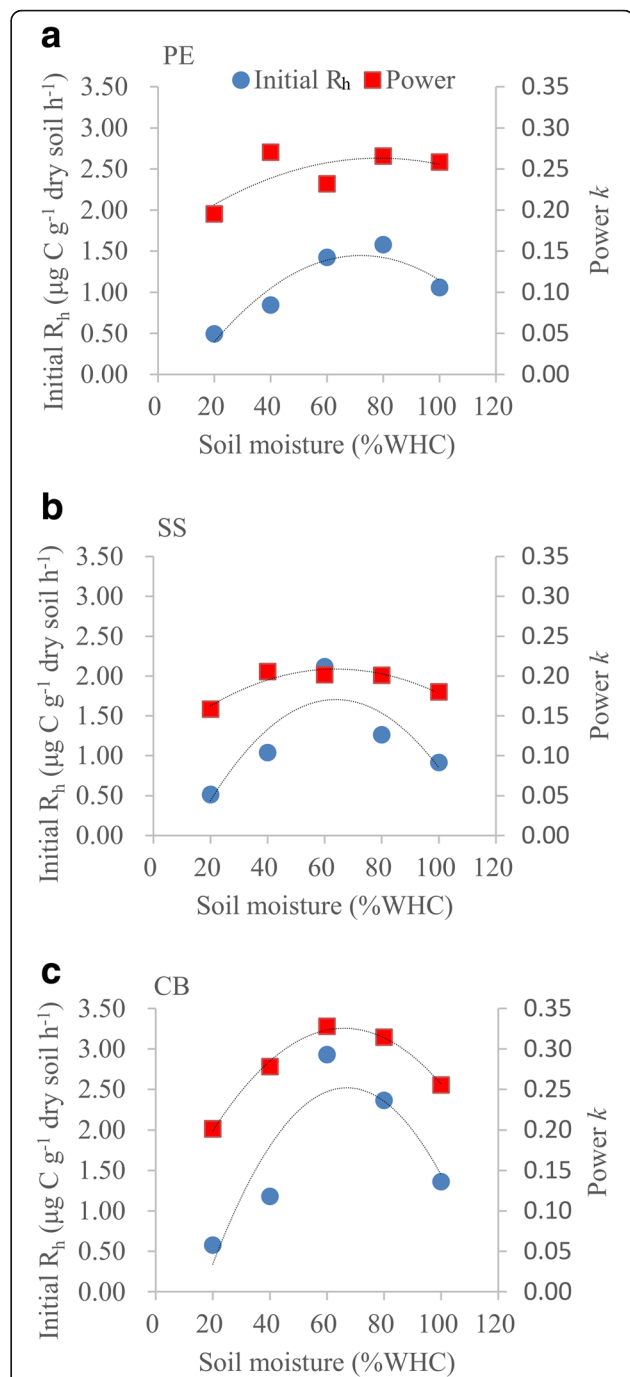
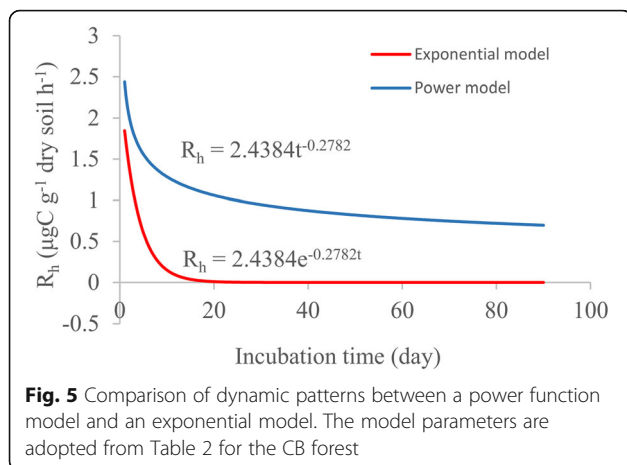


Fig. 4 Empirical relations between the power model parameters (R_1 and k) and soil moisture (M) in three subtropical forest soils. R_1 is the initial respiration, i.e., the starting value of R_h when $t = 1$; k is the power indicates the rate of R_h change. PE, SS, and CB in panels **a-c** represent the *P. elliotii* plantation, *S. superba* plantation, and conifer and broadleaf mixed forest soils, respectively. Models of fitting for PE, $R_1 = -3.868 W^2 + 5.572 W - 0.561$ ($r^2 = 0.89$), $k = -0.165 W^2 + 0.2659 W + 0.162$ ($r^2 = 0.54$); for SS, $R_1 = -6.576 W^2 + 8.403 W - 0.979$ ($r^2 = 0.76$), $k = -0.237 W^2 + 0.304 W + 0.111$ ($r^2 = 0.88$); for CB, $R_1 = -9.864 W^2 + 13.214 W - 1.907$ ($r^2 = 0.82$), $k = -0.598 W^2 + 0.790 W + 0.065$ ($r^2 = 0.99$)



With respect to soil moisture treatments, the two parameters of the power function model showed different response patterns compared with those to temperature treatments. At a low soil moisture (e.g., 20% WHC), SOC decomposition may be limited by water availability. At a high soil moisture (e.g., 100% WHC), it may be limited by oxygen availability. Thus, soil microbes are often more active at medium soil moistures (Bauer et al. 2008; Craine and Gelderman 2011; Davidson et al. 2012). This explains why the values of R_1 and k were the highest when soil moisture was at 60% WHC (Fig. 4). Relative to that of R_1 , the response pattern of k was less curving, indicating that k was less sensitive to moisture changes.

Forest type had significant effects on k but not on R_1 . Previous studies reported that plant species and soil biological communities could affect soil respiration through altering soil physicochemical properties (Monokrousos et al. 2004; Wei et al. 2015). The three forests in this study differed in their dominant tree species and soil properties, with CB having the highest soil TOC, TN and TP, and SS having the lowest ones. Although we found no significant forest type effects on R_1 , it did vary among forest types (Figs. 3 and 4). The mechanisms underlying the influence of forest type on the model parameters R_1 and k need to be better understood in order to explain the R_h variations across ecosystem types.

Conclusions

Compared with the widely used exponential decay model, the power function model performed better in quantitatively describing the change of R_h with incubation time under a wide range of temperature (10–38 °C) and moisture (20–100% WHC) conditions in three subtropical forest soils. The two key parameters (R_1 and k) of the power function model had a linear relationship with temperature but a quadratic relationship with moisture. The empirical relations derived from this incubation study provide important insights for developing and

parameterizing more mechanistic process-based ecosystem models. However, the generality of these empirical relations should be further tested under field conditions for the purpose of simulating soil R_h responses to climate changes in subtropical forests. Why and how the parameters vary with other soil properties such as substrate availability, microbial diversity and community composition, and the structural and functional properties of plant communities are the prior questions towards a better understanding to the mechanisms underlying the R_h responses to climate changes.

Abbreviations

BD: Soil bulk density; CB: Subtropical coniferous and broadleaf mixed forest; PE: *Plantation of Pinus elliottii*; SS: *Plantation of Schima superba*; TN: Total nitrogen; TOC: Total organic carbon; TP: Total phosphorus; WHC: Water holding capacity

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Authors' contributions

DH and WS designed the study. WZ and JH conducted the laboratory experiment. WZ and DH analyzed the data. DH, WZ, and WS wrote the manuscript. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing financial interests. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

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