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Spatio-Temporal Variability of Soil Respiration of Forest Ecosystems in China: Influencing Factors and Evaluation Model

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Abstract Understanding the influencing factors of the spatio-temporal variability of soil respiration (R_s) across different ecosystems as well as the evaluation model of R_s is critical to the accurate prediction of future changes in carbon exchange between ecosystems and the atmosphere. R_s data from 50 different forest ecosystems in China were summarized and the influences of environmental variables on the spatio-temporal variability of R_s were analyzed. The results showed that both the mean annual air temperature and precipitation were weakly correlated with annual R_s, but strongly with soil carbon turnover rate. R_s at a reference temperature of 0°C was only significantly and positively correlated with soil organic carbon (SOC) density at a depth of 20 cm. We tested a global-scale R_s model which predicted monthly mean R_s ($R_{s,monthly}$) from air temperature and precipitation. Both the original model and the reparameterized model poorly explained the monthly variability of R_s and failed to capture the inter-site variability of R_s. However, the residual of $R_{s,monthly}$ was strongly correlated with SOC density. Thus, a modified empirical model (TPS model) was proposed, which included SOC density as an additional predictor of R_s. The TPS model explained monthly and inter-site variability of R_s for 56% and 25%, respectively. Moreover, the simulated annual R_s of TPS model was significantly correlated with the measured value. The TPS model driven by three variables easy to be obtained provides a new tool for R_s prediction, although a site-specific calibration is needed for using at a different region.

Keywords Soil respiration · Soil organic carbon · Climate · Forest ecosystem · China

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Introduction

Soil respiration (R_s) is the second largest carbon flux between terrestrial ecosystems and the atmosphere producing 79.3–81.8 Pg C annually (Raich and others 2002), which is more than 10 times of the current rate of fossil fuel combustion (Marland and others 2000). R_s contributes 30–80% of annual ecosystem respiration (Davidson and others 2006), which is likely to be the main determinant of carbon balance of different ecosystems (Valentini and others 2000). Thus, understanding the influencing factors of the spatio-temporal variability of R_s, as well as the evaluation model of R_s is critical to the accurate prediction of future changes in carbon exchange between ecosystems and the atmosphere (Flanagan and Johnson 2005).

Disagreements remain over the major factors influencing the variability of R_s at different temporal or spatial scales (Reichstein and others 2003). For example, several studies suggested that air temperature and precipitation were the two major factors influencing the spatio-temporal variability of R_s at the global scale (Raich and Schlesinger 1992; Raich and Potter 1995). However, Janssens and others (2001) found the correlation between annual R_s and annual soil temperature was weak among 18 forest ecosystems in Europe. In stead, they found the annual gross primary productivity (i.e., the total amount of carbon fixed during photosynthesis) had a significantly positive impact on the annual R_s. This result was consistent to the study on R_s of 31 terrestrial ecosystems in Europe and North America (Hibbard and others 2005) and the comparing study in broadleaved and needle-leaf forest stands (Moyano and others 2008). Furthermore, some studies reported a remarkably positive correlation between R_s and soil organic carbon (SOC) density (Smith 2003; Gough and Seiler 2004; Rodeghiero and Cescatti 2005; Wang and Yang 2007).

With regard to the statistical model for R_s prediction, Raich and others (2002) suggested a simple empirical R_s model driven by monthly air temperature and monthly precipitation for evaluating the spatio-temporal pattern of R_s at the global scale. However, the model failed to capture the monthly and inter-site variability of R_s of forest ecosystems in Europe and North America (Reichstein and others 2003). After the maximum leaf area index was included as an additional predictor of R_s, the explanation of the modified model for month-to-month and inter-site variability obviously increased (Reichstein and others 2003). Therefore, global-scale model only considering temperature and precipitation as the factors may need to be modified to include more factors for better prediction of the spatio-temporal variability of R_s at ecosystem to regional scale.

In China, scattered R_s measurements have been made in the last 10 years; and in recent years, ChinaFLUX has made continuous measurements of R_s over typical forest, grassland and cropland ecosystems in China (Wang and Wang 2003, Yu and others 2006), which provide rich data for the study of the spatio-temporal variability of R_s in China and its environmental constraints, as well as the regional-scale evaluation model of R_s. In this study, R_s data of ChinaFLUX and previously published data were summarized, (1) to examine the temporal (monthly and annual) and spatial variability of R_s of forest ecosystems in China and its environmental constraints; and (2) to test whether the global-scale model suggested by Raich and others (2002) can be used to describe the spatio-temporal variability of R_s of forest ecosystems in China and then modify it.

Data Sources and Processing

Data Sources

R_s was measured at 5 forest sites of ChinaFLUX (Changbaishan, Qianyanzhou, Dinghushan, Heshan, Xishuangbanna). Furthermore, R_s data measured at 11 forest sites in China was collected from previously published literature. Figure S1 (see supplementary materials) shows the spatial distribution of the above 16 sites in China, including 50 forest ecosystems belonging to seven forest types (i.e., tropical forest (TPF), evergreen needle-leaf forest (ENF), evergreen broadleaved forest (EBF), deciduous needle-leaf forest (DNF), deciduous broadleaved forest (DBF), mixed forest (MXD), subalpine forest on the Tibetan Plateau (APF)). These sites were located in the main climatic zones of China, spanning from alpine via temperate to tropical. Table S1 (see supplementary materials) presents the site specific information, including ecosystem types, climates, soil characteristic, and measurement periods for R_s.

Measurements of R_s

R_s was measured either by static chamber/gas chromatography (GC) method or by dynamic chamber/IRGA method, which were the two most popular methods for R_s measurements in China. Although intercalibration of the different chamber techniques was impossible, nevertheless, several studies report that the measurement difference is small ($\sim$10%) between the static chamber method and dynamic chamber method with the CO_2 concentration measured by the LI-6400 system (Kou and others 2007) and the comparability of R_s measured from different methods is ensured. R_s data in this study were required to be measured between 9:00 am–11:00 am (China Standard Time, CST) for fluxes of soil CO_2 measured during this period were close to daily means at our measured sites and in other studies (Dugas and others 1999; Mielnick and Dugas 2000), with 4–6 collars randomly inserted into the soil in each ecosystem and measured 2–3 times per month. Detailed information on R_s measurement and data processing are described in Wang and Wang (2003) and in the references in Table S1 (see supplementary materials).

Data Processing

The R_s data were classified into two time scales: monthly mean R_s and annual R_s. Monthly mean R_s was compiled in the same way as Raich and others (2002), i.e., all available soil respiration observations were averaged per month and ecosystem, then R_s data in the same month of different years was averaged to obtain monthly R_s. Moreover, monthly mean R_s data in literature derived from R_s equation were not included in this study. Annual R_s, was either collected from the literature or estimated from linear interpolation of collected daily R_s. The annual R_s values of different years were averaged.

Environmental variables used in the analysis were as followings: (1) monthly temperature and monthly precipitation were obtained from direct observations at each meteorological site or interpolation climate data from 678 meteorological sites using ANUSPLIN 3.1 (Hutchinson 1998); mean annual temperature and annual precipitation were derived from literature directly; (2) SOC density at a depth of 20 cm, root biomass (t $\mathrm{Cha^{-1}}$) and annual litterfall (g $\mathrm{Cm^{-2}y^{-1}}$) were extracted from the corresponding literature if not directly available from the sites. Soil organic material was oven dried at 80°C for dry weight determination and SOC density was determined by potassium bichromate titrimetric method. Biomass estimation was according to the regression models relating tree biomass to diameter at the breast height. Litterfall was determined with harvest method: litterfall was collected at an interval of one-month with 2–3 sampling points in each field throughout the whole year and dried to estimate dry weight.

R_s Model

Exponential equations are commonly used to quantify the dependence of R_s on temperature in ecosystems without stresses of water or other factors. The van't Hoff equation (Eq. 1; Lloyd and Taylor 1994) is the most popular exponential function to describe the relationship between R_s and temperature,

$$R_s = R_0 e^{bt} \tag{1}$$

where R_s is the instantaneous soil respiration rate (μmol $\mathrm{m^{-2}\ s^{-1}}$), t is the temperature (°C), and R_0 is soil respiration rate at a reference temperature of 0°C (μmol $\mathrm{m^{-2}\ s^{-1}}$). In some collected literature, Eq. 1 is also used for analyzing the response of R_s to temperature. In that case, several R_0 values in this study were derived directly from the literature.

Equations 2 and 3 were used to analyze the response of monthly mean R_s to monthly temperature and monthly precipitation, respectively.

$$R_{s,\mathrm{monthly}} = Fe^{QT} \tag{2}$$

$$R_{s,\mathrm{monthly}} = P_0 + P/(P+K) \tag{3}$$

where $R_{s,\mathrm{monthly}}$ is the monthly mean R_s rate (g $\mathrm{Cm^{-2}\ d^{-1}}$), and T and P are the monthly air temperature and monthly precipitation, respectively, F is the monthly mean R_s rate when monthly air temperature is 0°C, Q is the temperature sensitivity of R_s, and P_0 and K are regression parameters.

Raich and others (2002) evaluated the spatio-temporal pattern of the global R_s with Eq. 4 (TP model),

$$R_{s,\mathrm{monthly}} = Fe^{QT}P/(P+K) \tag{4}$$

where the definitions of variables and parameters in Eq. 4 are similar to those in Eqs. 2 and 3.

In this study, we first tested the ability of the TP model for estimating the spatio-temporal variability of R_s of forest ecosystems in China with the original parameters suggested by Raich and others (2002) ($F = 1.250$; $Q = 0.055$; $K = 4.250$). Additionally, the model was reparameterized (TP2 model) by calculating a nonlinear least squares fit of the parameters to our dataset ($F = 1.608$, $Q = 0.034$, $K = 0.334$).

At last, a modified R_s model was proposed (TPS model, Eq. 5), in which the parameter F in Eq. 4 was modified as a linear function of SOC density,

$$R_{s,\mathrm{monthly}} = (R_{\mathrm{SOC}=0} + M \cdot \mathrm{SOC})e^{QT}(P+P_0)/(P+K) \tag{5}$$

Table 1 The statistics of annual R_s of forest ecosystems

Forest type	Annual R_s (g $\mathrm{Cm^{-2}\ y^{-1}}$)					
	Mean	SD	CV (%)	Min	Max	*n*
TRF	1274	NA	NA	NA	NA	1
ENF	578	202	35.1	237	976	14
EBF	923	578	62.6	526	1586	3
DNF	560	145	25.9	403	688	3
DBF	684	224	32.7	309	1105	15
MXD	887	151	17.0	651	1001	5
APF	875	328	37.5	395	1597	11
All	745	297	39.8	237	1597	50

TRF tropical forest, *ENF* evergreen needle-leaf forest, *EBF* evergreen broadleaved forest, *DNF* deciduous needle-leaf forest, *DBF* deciduous broadleaved forest, *MXD* mixed forest, *APF* subalpine forest on the Tibetan Plateau where $R_{soc=0}$ is the $R_{s,monthly}$ rate when the SOC density is zero. Here, similar to Reichstein and others (2003), another parameters P_0 was added into the TPS model for taking into account the capability of soil to maintain water, which means that when the monthly precipitation was zero, the soil could still effuse CO_2 (Reichstein and others 2003).

Results

Factors Influencing the Spatial Variability of Annual R_s

The mean annual R_s of 50 forest ecosystems was 745 ± 297 g Cm^{-2} y^{-1}, ranging from 237 to 1597 g Cm^{-2} y^{-1} (Table 1). Mean annual R_s among different forest types showed an order of TRF > EBF > MXD > APF > DBF > ENF > DNF, meaning that the annual R_s of evergreen forest was higher than that of deciduous forest and the annual R_s of broadleaved forest was higher than that of needle-leaf forest.

The correlation analysis between the annual R_s and environmental factors showed that the annual R_s was weakly correlated with mean annual air temperature (MAT), mean annual precipitation (MAP) and SOC density at a depth of 20 cm, but strongly correlated with the root biomass (Fig. 1a–d). Moreover, the annual R_s was significantly correlated with the annual litterfall among 23 forest ecosystems having litterfall records, with a correlation coefficient of 0.57.

The ratio of annual R_s to soil carbon density (including roots) is taken as soil carbon turnover rate. This ratio was strongly correlated with mean annual air temperature and mean annual precipitation (Fig. 2), showing that the soil

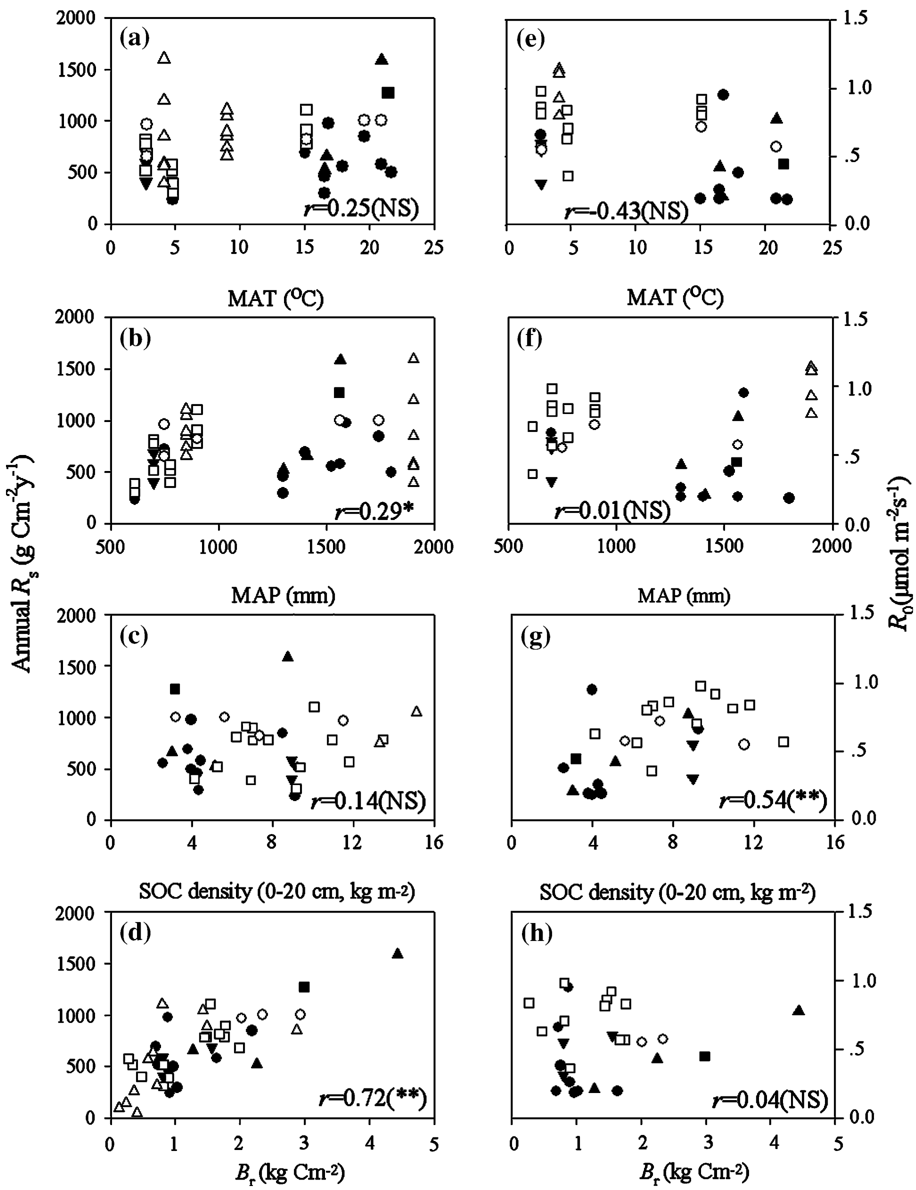


Fig. 1 The relationships between R_s on the annual basis (**a–d**), R_s rate at a reference temperature of 0°C (R_0) (**e–h**) and its influencing factors (mean annual temperature (MAT), mean annual precipitation (MAP), soil organic carbon (SOC) density at a depth of 20 cm, root biomass (B_r)) of forest ecosystems in China. *Filled square* tropical forest; *filled circle* evergreen needle-leaf forest; *filled triangle* evergreen broadleaved forest; *filled inverted triangle* deciduous needle-leaf forest; *open square* deciduous broadleaved forest; *open circle* mixed forest; *open triangle* subalpine forest on the Tibetan plateau

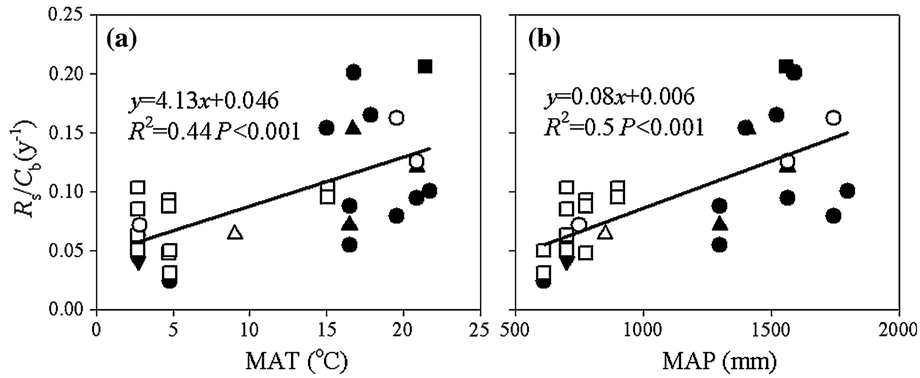
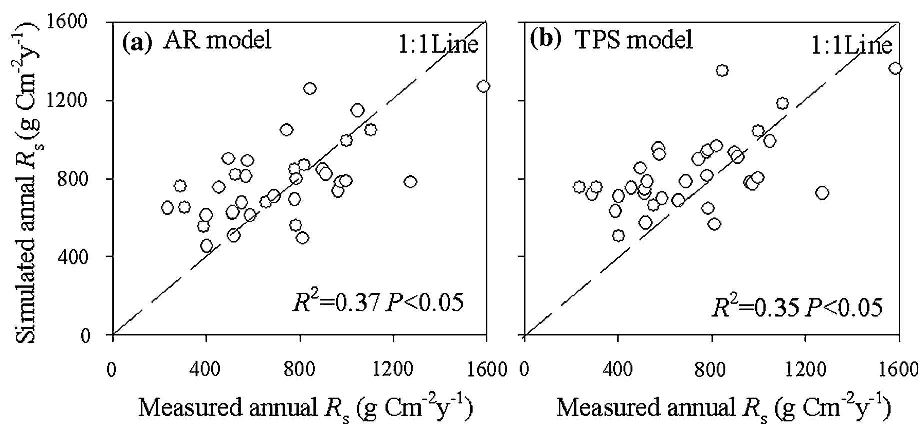


Fig. 2 The influences of MAT and MAP on the turnover rate of soil organic carbon (C_b, including root biomass). The turnover rate was the ratio of annual R_s to C_b. *Filled square* tropical forest; *filled circle* evergreen needle-leaf forest; *filled triangle* evergreen broadleaved forest; *filled inverted triangle* deciduous needle-leaf forest; *open square* deciduous broadleaved forest; *open circle* mixed forest; *open triangle* subalpine forest on the Tibetan plateau

Fig. 3 The comparison between measured annual R_s and simulated annual R_s of forest ecosystems (**a** AR model; **b** TPS model)



carbon turnover rates of the ecosystems with warm and wet climates were higher than those of the ecosystems with cold and dry climates.

The influence of one factor to R_s is always confounded by other factors, because the environmental factors influencing R_s are always correlated with each other. Thus, inter-site comparison of R_s is often based on the soil efflux at a reference temperature or soil moisture (Reichstein and others 2003; Hibbard and others 2005; Rodeghiero and Cescatti 2005; Sampson and others 2007). Figure 1e–h show the influences of MAT, MAP, SOC density and root biomass on R_s rate at a reference temperature of 0°C (i.e., R_0). The results showed that R_0 was only significantly and positively correlated with SOC density with a correlation coefficient of 0.54. The linear correlation between SOC density and R_0 provided a valuable reference for the modification of regional-scale R_s model. A multiple regression was conducted to describe the relationship between the annual R_s and its major controlling factors (MAT, MAP and SOC density at a depth of 20 cm), and an empirical model (AR model, Eq. 6) was obtained,

$$R_s = (1.55\mathrm{SOC} + 8.65)(1.13\mathrm{MAT} + 0.01\mathrm{MAP} + 16.35)$$
$$R^2 = 0.37 \qquad (6)$$

Figure 3a shows the comparison of measured annual R_s and simulated annual R_s of AR model. The AR model explains 37% of spatial variation of annual R_s of forest ecosystems in China.

Factors Influencing the Seasonal Variation of Monthly R_s

The $R_{s,\mathrm{monthly}}$ increased exponentially with the increase of monthly air temperature (Fig. 4a). Regardless of forest types, monthly air temperature explained 20.5% of variability of $R_{s,\mathrm{monthly}}$; however, for different types, about 25.3–91.2% of variability in $R_{s,\mathrm{monthly}}$ could be explained by monthly air temperature (Table 2), indicating that other environmental factors influenced the variability of $R_{s,\mathrm{monthly}}$ depending on different types of forest ecosystems. The $R_{s,\mathrm{monthly}}$ at a reference temperature of 0°C (i.e., the parameter F in Eq. 2) of the deciduous broadleaved forest in the

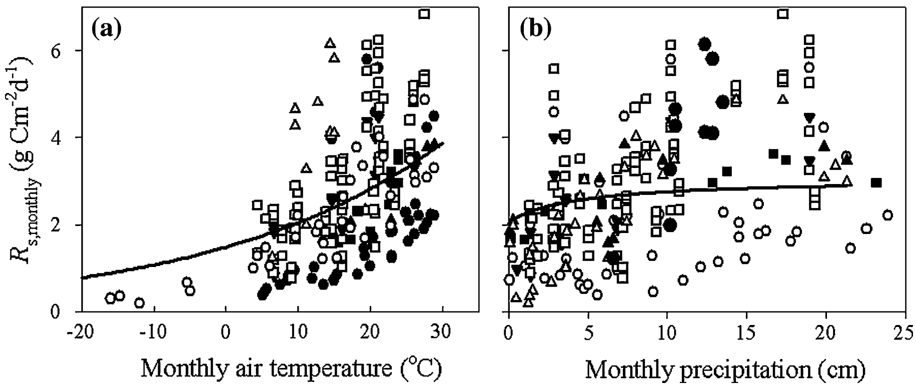


Fig. 4 The influences of monthly air temperature (**a**) and monthly precipitation (**b**) on the monthly mean R_s ($R_{s,monthly}$). The curves in **a** and **b** were fitted with Eqs. 2 and 3, respectively. The regression coefficients were shown in Table 2. *Filled square* tropical forest; *Filled circle* evergreen needle-leaf forest; *Filled triangle* evergreen broadleaved forest; *filled inverted triangle* deciduous needle-leaf forest; *open square* deciduous broadleaved forest; *open circle* mixed forest; *open triangle* subalpine forest on the Tibetan Plateau

Table 2 The parameter values of temperature and precipitation-response functions

Forest type	Eq. 2			Eq. 3		
	F	*Q*	R^2	P_0	*K*	R^2
TRF	0.437	0.084	0.808	2.055	4.594	0.493
ENF	0.717	0.05	0.253	1.416	6.086	0.060
EBF	0.742	0.057	0.912	2.177	5.840	0.270
DNF	0.668	0.085	0.797	2.260	3.558	0.232
DBF	1.097	0.077	0.821	3.709	5.382	0.161
MXD	1.002	0.049	0.732	1.711	4.46	0.237
APF	1.304	0.092	0.452	3.498	9.601	0.530
All	1.485	0.032	0.203	2.065	4.420	0.110

TRF tropical forest, *eNF* evergreen needle-leaf forest, *EBF* evergreen broadleaved forest, *DNF* deciduous needle-leaf forest, *DBF* deciduous broadleaved forest, *MXD* mixed forest, *APF* subalpine forest on the Tibetan Plateau

temperate zone and the subalpine forest in the alpine zone was higher than those of the forest ecosystems in subtropical and tropical zones, and so was the temperature sensitivity index (i.e., the parameter *Q* in Eq. 2) (Table 2).

The relationship between $R_{s,monthly}$ and monthly precipitation across all types of forest ecosystems was hyperbolic (Fig. 4b), i.e. $R_{s,monthly}$ increased with the monthly precipitation and reached a stable value when the monthly precipitation exceeded a threshold value.

The Evaluation Model for Describing the Spatio-Temporal Variability of R_s

To quantitatively evaluate the spatio-temporal variability of R_s, we first tested a global-scale R_s model proposed by Raich and others (2002) (TP model). Both the original TP model and the reparameterized TP model (TP2 model) explained less than 35% of the spatio-temporal variability of $R_{s,monthly}$ (Fig. 5a, b, Table 3).

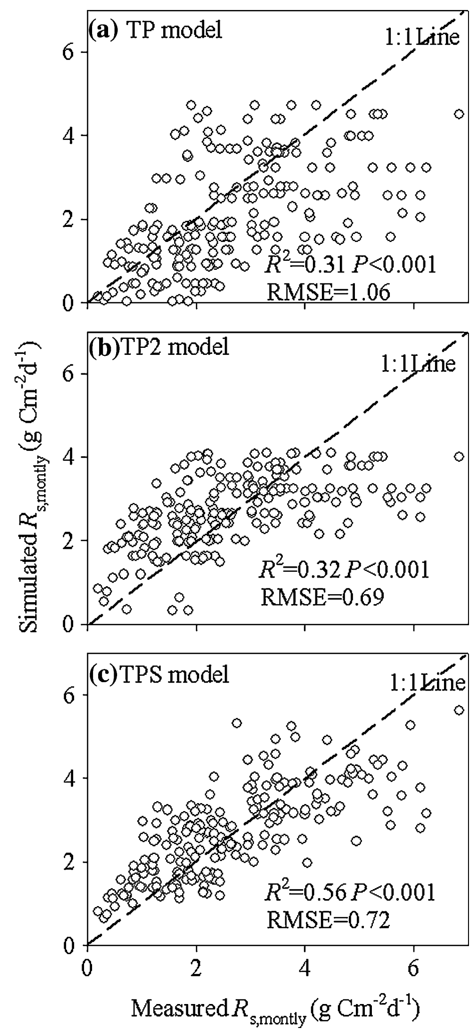


Fig. 5 The relationship between measured $R_{s,monthly}$ and simulated $R_{s,monthly}$ of forest ecosystems (**a** TP; **b** TP2; **c** TPS)

To analyze the capacities of the TP and TP2 models for explaining the inter-site variability of $R_{s,monthly}$, $R_{s,monthly}$ values of different months per ecosystem were averaged.

Table 3 The parameter values of R_s model

Model	$R_{soc=0}$	M	F	Q	P_0	K	RMSE	R^2
TP	NA	NA	1.250	0.055	NA	4.250	1.06	0.31
TP2	NA	NA	1.608	0.034	NA	0.334	0.69	0.32
TPS	0.584	0.129	NA	0.043	2.706	4.661	0.72	0.56

However, the correlation coefficient between the average measured values and average simulated values was near zero (Figures not shown here), meaning that nearly no inter-site variability of $R_{s,monthly}$ was explained by the TP and TP2 models. However, the residual of simulated $R_{s,monthly}$ was strongly correlated with SOC density at a depth of 20 cm (Fig. 6), indicating that the SOC density was an additional predictor of the spatial variability of monthly R_s, which was consistent with the result that SOC density had a strong influence on the spatial variability of the annual R_s of forest ecosystems in China (Fig. 1g).

According to the above results, TPS model was proposed (Eq. 5) and the parameter values are shown in Table 3. The comparison of measured $R_{s,monthly}$ and simulated $R_{s,monthly}$ of the TPS model showed that the TPS model explained 56% of the monthly variability of $R_{s,monthly}$ (Fig. 5c, Table 3), and the comparison of averaged measured $R_{s,monthly}$ and averaged simulated $R_{s,monthly}$ showed that the TPS model explained 25% of the inter-site variability (Fig. 7). This suggested that after the modification of model structure and parameters, the TPS model explained more spatio-temporal variability of R_s of forest ecosystems in China than the TP and TP2 models. Moreover, the TPS model showed an explanation comparable to the AR model of the spatial variability of annual R_s across forest ecosystems in China (Fig. 3).

Discussions

The Influence of Temperature on R_s

Temperature has been documented as the primary factor influencing seasonal variability of R_s of ecosystems in relatively humid regions (Lloyd and Taylor 1994), and our study also found that monthly air temperature explained 25.3–91.2% of the variability of monthly mean R_s for the seven types of forest ecosystems in China (Table 2). However, there are still disagreements on whether temperature is the major factor directly influencing the spatial variability of R_s at regional scales (Janssens and others 2001; Raich and Schlesinger 1992; Rodeghiero and Cescatti 2005). Raich and Schlesinger (1992) found that annual R_s was significantly and positively correlated with mean annual air temperature at the global scale. However, Janssens and others (2001) found that the correlation between annual R_s and annual soil temperature was weak among 18 forest ecosystems in Europe. Our study on the R_s of forest ecosystems in China also suggested that the correlation between annual R_s and mean annual air temperature was weak (Fig. 1a) and monthly air temperature could explain only 20.3% of the overall variability of $R_{s,monthly}$ in China (Table 2). These results suggest that temperature is not always the direct factor controlling the spatial variability of R_s on regional scales, and indicates that other factors may be more important in controlling R_s among sites at regional scale.

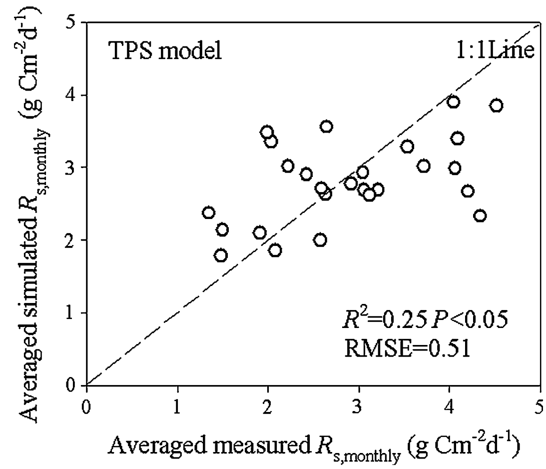


Fig. 7 The comparison of averaged measured $R_{s,monthly}$ and averaged simulated $R_{s,monthly}$ of the TPS model

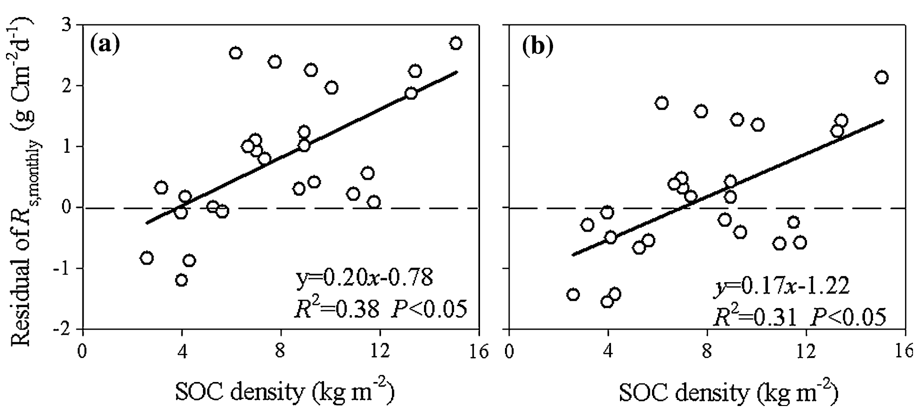


Fig. 6 The relationship between SOC density at a depth of 20 cm and residual of simulated $R_{s,monthly}$ (**a** TP; **b** TP2). Residual of simulated $R_{s,monthly}$ values were averaged within each ecosystem

The Influence of Precipitation on R_s

Soil moisture, aridity index and precipitation are always used as surrogates of ecosystem moisture status, which are also other important factors controlling the variations of R_s (Raich and Schlesinger 1992; Raich and Potter 1995; Davidson and others 1998; Reichstein and others 2003). However, to obtain accurate soil moisture at a regional scale remains difficult, thus precipitation is commonly used as a surrogate for ecosystem moisture status in regional-scale studies (Raich and Schlesinger 1992; Raich and Potter 1995). Our study indicated that soil still could release CO_2 even when the monthly precipitation was zero (Fig. 4b), which was consistent with the study of Reichstein and others (2003). The TP model, having the implicit assumption of "zero-precipitation-zero-respiration", decreased model precision. Thus, the R_s model should take into account the soil water-holding capacity while keeping accumulated precipitation from the previous month when the influence of precipitation on R_s is simulated (Reichstein and others 2003). Our TPS model stressed the importance of soil water storage for R_s in this study. However, the capacity of soil CO_2 efflux tended to stabilize when the monthly precipitation exceed a threshold value; in addition, the correlation between R_s and precipitation was weak (Fig. 4b). So when the monthly precipitation is too high, precipitation may not be a suitable variable representing the moisture status of studied ecosystems. Further studies on seeking a more suitable variable are needed.

The Influence of Soil Organic Carbon Density on R_s

Several studies report good correlation between R_s and SOC density (Rodeghiero and Cescatti 2005; Wang and Yang 2007), suggesting a certain influence of SOC density on the spatial variability of R_s. Rodeghiero and Cescatti (2005), adopting standardized measurement methods of R_s and SOC density, found that the R_s rate at a reference temperature of 10°C was significantly and positively correlated with SOC at a depth of 30 cm among 11 forest ecosystems along an elevation/temperature gradient in the Italian Alps. Wang and Yang (2007) reported the heterotrophic R_s of 6 temperate forest ecosystems in North China were linearly correlated to SOC concentration in the surface layer. Our study also found the R_s rate at a reference temperature of 0°C was positively correlated with SOC density at a depth of 20 cm (Fig. 1g), and the residual of simulated $R_{s,monthly}$ of TP and TP2 models were correlated with SOC density (Fig. 6). The reference R_s rate varied among different types of forest ecosystems (Table 2), suggested that forest ecosystem in lower temperature climatic zone with higher SOC density had stronger potential for soil CO_2 release (Zheng and others 2009). These results suggest that as an important substrate for R_s, SOC density strongly influences the spatial variability of soil CO_2 efflux of terrestrial ecosystems in China and is a potential predictor for the spatio-temporal variability of R_s, which is valuable knowledge for the modification of regional-scale R_s models.

Regional-Scale Model of R_s

The interdependence among different process-based models limits the inter-comparison and validation, since they commonly rely on similar theories of carbon pool decomposition and distribution (Cramer and others 1999; Reichstein and others 2003). The simple empirical model, extracting the effects of environmental factors on R_s from the measured data, can provide a truly independent database of soil CO_2 emissions that can be used to corroborate the predications of more complex process-based R_s models (Raich and Potter 1995).

The major factors controlling the variability of R_s always vary with the studied scales or regions. The TP model, driven by monthly temperature and monthly precipitation, explained little of the variation of R_s of forest ecosystems in China (Fig. 5a, b), although it well evaluated the global variability of R_s (Raich and others 2002). Whereas, there were strong correlation between R_s and the root biomass (Fig. 1d) and also litterfall, suggesting the vital influence of root carbon matter and vegetation productivity on the spatial variability of R_s (Davidson and others 2002; Sampson and others 2007; Moyano and others 2008). However, these factors are not easy variables to obtain at regional scale, which limits the use of them in regional-scale R_s model.

In our study, the R_s rate at a reference temperature was described as a function of SOC density, and a modified R_s model (TPS model) was proposed which well explained the spatio-temporal variability of R_s of forest ecosystems in China (Figs. 5c, 7). The significant correlation between the simulated annual R_s of TPS model and the measured value (Fig. 3b) indicated that the TPS model with more mechanistic base was still suitable for the annual R_s modeling. This result suggested that the selection of the most crucial factors as predictors in the R_s model was more important than the selection of the model time step (Reichstein and others 2003). Since the TPS model is driven by climate variables and SOC which likely to be obtained from remote sensing (Zhou and others 2008), it provides a new tool for the quantitative evaluation of the spatio-temporal variability of R_s at regional scales. It is noticeable that a site-specific calibration (e.g., reparameterization) may be needed in order to use the model for a different region.

Conclusions

Based on the summarized R_s data from 50 different forest ecosystems in China, our study suggested SOC density, in addition to climatic variables, as a good predictor for the spatio-temporal variability of R_s of forest ecosystems in China, which is valuable knowledge for the modification of a regional-scale R_s model. A modified statistical model (TPS model) driven by monthly temperature, precipitation and soil organic carbon density was proposed, which well explained the spatio-temporal variability of R_s of forest ecosystems in China. Furthermore, the TPS model also well explained the spatial variation of annual R_s, although it runs at the monthly time step. However, the TPS model is only built from R_s data of ecosystems with good temperature and moisture conditions and SOC density limited to 0–15.09 kg m^{-2}, thus an evaluation of the TPS model in dry and cold zones or ecosystems with higher SOC density is necessary before applying it at larger scale.

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