Spatiotemporal Pattern of Soil Respiration of Terrestrial Ecosystems in China: The Development of a Geostatistical Model and Its Simulation

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Quantification of the spatiotemporal pattern of soil respiration \( R_s \) at the regional scale can provide a theoretical basis and fundamental data for accurate evaluation of the global carbon budget. This study summarizes the \( R_s \) data measured in China from 1995 to 2004. Based on the data, a new region-scale geostatistical model of soil respiration (GSMSR) was developed by modifying a global scale statistical model. The GSMSR model, which is driven by monthly air temperature, monthly precipitation, and soil organic carbon (SOC) density, can capture 64% of the spatiotemporal variability of soil \( R_s \). We evaluated the spatiotemporal pattern of \( R_s \) in China using the GSMSR model. The estimated results demonstrate that the annual \( R_s \) in China ranged from 3.77 to 4.00 Pg C yr\(^{-1}\) between 1995 and 2004, with an average value of 3.84 \pm 0.07 Pg C yr\(^{-1}\), contributing 3.92%–4.87% to the global soil CO\(_2\) emission. Annual \( R_s \) rate of evergreen broadleaved forest ecosystem was 698 \pm 11 g C m\(^{-2}\) yr\(^{-1}\), significantly higher than that of grassland (439 \pm 7 g C m\(^{-2}\) yr\(^{-1}\)) and cropland (555 \pm 12 g C m\(^{-2}\) yr\(^{-1}\)). The contributions of grassland, cropland, and forestland ecosystems to the total \( R_s \) in China were 48.38 \pm 0.35%, 22.19 \pm 0.18%, and 20.84 \pm 0.13%, respectively.

1. Introduction

Soil respiration is a major process of carbon dioxide emission from terrestrial ecosystems to atmosphere (1). Thus, quantifying the spatiotemporal pattern of soil respiration \( R_s \) at the regional or continental scale is critical to establish an experimental and theoretical basis for accurate assessment of the global carbon budget. Three major approaches are available for estimating \( R_s \) at the regional scale. The inventory method multiplies the mean \( R_s \) rates of each land cover type by its area. Then, the total of the CO\(_2\) emissions from different land covers is taken as the total \( R_s \) (2). The second method calculates the \( R_s \) and its spatiotemporal variability using a process-based model (3). The third uses geostatistical model of \( R_s \), which is constructed based on the relationships between environmental variables and measured soil carbon flux (4, 5).

Each method has weakness and uncertainties. The inventory method is limited by the quality and the spatiotemporal representativeness of measured \( R_s \) data. Poor data can result in infinite uncertainty on \( R_s \) estimates at the regional scale. The process-based \( R_s \) model can simulate the spatial patterns and also predict the long-term dynamics of ecosystem \( R_s \) (6). However, the process-based \( R_s \) model has complicated structure in coupling with soil—plant—atmosphere processes. It is thus difficult to evaluate the rationality of the estimated results when considerable large uncertainty exists in the spatial representativeness of model parameters. Relatively, the geostatistical \( R_s \) model has simple structure, sound parameterization method, and reasonable results (4, 7), though it cannot predict \( R_s \) changes with climate, nitrogen deposition, etc. It is usually built on the relationships between in situ \( R_s \) rates and environmental variables, such as temperature, precipitation, and leaf area index (LAI). In addition, the geostatistical model can validate the process-based \( R_s \) model by providing independent data on soil CO\(_2\) emissions. Therefore, the geostatistical \( R_s \) model is most widely used in the quantification of spatiotemporal variability of \( R_s \) at regional scale (4).

Progress has been made on the research of \( R_s \) quantification in China over the past decade. Fang et al. estimated the annual \( R_s \) of terrestrial ecosystems in China using the inventory method (8). Zhou et al. inversely simulated the spatial pattern of heterotrophic respiration using remote sensing data and climatic data (9). Cao et al. evaluated the spatiotemporal pattern of heterotrophic respiration of Chinese terrestrial ecosystems based on a process-based model (i.e., CEVS model) (3). Continuous measurements of \( R_s \) over typical forestland, grassland, and cropland ecosystems in China provide abundant data for evaluating the spatiotemporal variability of \( R_s \) in China and its environmental constraints as well as the region-specific behaviors of geostatistical model of \( R_s \) (10, 11). By synthesizing the measured \( R_s \) data of ChinaFLUX and the \( R_s \) data from the published literature, Zheng et al. found that the spatial variability of \( Q_{10} \) of \( R_s \) in China was determined by soil temperature, soil organic carbon (SOC) density, and ecosystem type, and that the spatial pattern of \( Q_{10} \) could be described as an exponential function of soil temperature (12). Based on the \( R_s \) database of ChinaFLUX, Zheng et al. tested the applicability of a global-scale \( R_s \) model presented by Raich (5) (hereafter called TP model) to quantification of the spatiotemporal variability of \( R_s \) of forest ecosystems in China (13). In their study, the TP model was modified into an empirical statistical model, which is driven by monthly air temperature, monthly precipitation, and SOC density (13).

This study summarizes the \( R_s \) data set of the ChinaFLUX and the published data in China over the past decade. The objectives were (1) to test whether the model by Raich et al. (5) could be used to describe the spatiotemporal variation of \( R_s \) in China and, if not, how to modify it; (2) to construct...
a geostatistical model of $R_c$ (GSMSR) driven by air temperature, precipitation, and SOC density; and (3) to evaluate the temporal (seasonal and interannual) and spatial variability of $R_c$ in China from 1995 to 2004 and the contribution of $R_c$ in China to the global soil carbon emission.

2. Data Sources and Model Development

2.1. Collection and Integration of $R_c$ Measurement Data in China. In this study, an $R_c$ database of China was established by synthesizing the $R_c$ data set of ChinaFLUX and those published in approximately 200 papers in the literature. To ensure the comparability of the measured $R_c$, we only selected the data measured using static chamber/GC method and static/dynamic chamber/IRGA method (13). The selected $R_c$ data sets were built at both monthly and annual scales.

The monthly $R_c$ were compiled in the same way as used by Raich et al. (5). All available $R_c$ observations were averaged per month and ecosystem, then $R_c$ data in the same month of different years were averaged to obtain monthly mean $R_c$. Note that the monthly $R_c$ data derived from $R_c$ equations in the literature were not included in our database. In total, 390 monthly $R_c$ data observed at 21 sites and 40 ecosystems were obtained (Figure 1a). The annual $R_c$ data were either collected from the literature or estimated from the linear interpolation of collected daily $R_c$. The annual $R_c$ values of different years were averaged for each ecosystem. A total of 50 annual $R_c$ data for 26 sites were collected (Figure 1b).

2.2. Data Spatialization and Processing of Environmental Variables. To quantify the spatiotemporal pattern of $R_c$ (1 km × 1 km, monthly scale) and the variables driving the model, we spatialized the data of the following environmental variables. Grid monthly air temperature and monthly precipitation (1 km × 1 km) were interpolated from climate data of 678 meteorological sites using a specially designed interpolation package for meteorological data ANUSPLIN 3.1 (14). Grid SOC density data at a depth of 20 cm (1 km × 1 km) were obtained based on the interpolation from the 1:40000000 SOC density vector data (15). Grid land cover data (1 km × 1 km) were derived by distilling China from the global grid land cover data (16).

2.3. Construction of the Geostatistical $R_c$ Model of China. (1) Test of the Capability of a Global-Scale $R_c$ Model. The $R_c$ equations based on Lloyd and Taylor (17) include the van’t Hoff, Arrhenius, and Lloyd–Taylor equations. We compared the three equations, and found that no significant difference existed among the results, therefore, we used the van’t Hoff equation to quantify the dependence of $R_c$ on temperature (eq 1) because the majority of our studied ecosystems, which were free of the stresses of water and other environmental factors, had a fixed temperature sensitivity.

$$R_c = R_{0c}e^{Q_T}$$

(1)

where $R_c$ is the instantaneous soil respiration rate (µmol m$^{-2}$ s$^{-1}$), $R_0$ is soil respiration rate at a reference temperature of 0 °C (µmol m$^{-2}$ s$^{-1}$), and $T$ is actual air temperature (°C).

The following two equations were used to analyze the response of monthly $R_c$ to temperature and precipitation, respectively (5),

$$R_{c,Monthly} = R_0e^{Q_TT}$$

(2)

$$R_{c,Monthly} = P_0 + P(T + K)$$

(3)

where $R_{c,Monthly}$ is monthly mean $R_c$ rate (g C m$^{-2}$ d$^{-1}$), $T$ is monthly air temperature, $P$ is monthly precipitation, $Q$ is temperature sensitivity of $R_c$, and $P_0$ and $K$ are regression parameters.

Raich et al. (5) presented TP model (eq 4) to evaluate the impacts of temperature and precipitation on the spatiotemporal pattern of the global $R_c$.

$$R_{c,Monthly} = R_0e^{Q_T(P + K)}$$

(4)

where the definitions of variables and parameters are the same as those in above equations. The values of parameters are $R_0 = 1.250$, $Q = 0.055$, and $K = 4.25$ (5).

In this study, the ability of TP model for estimating the spatiotemporal variability of $R_{c,Monthly}$ was tested using the above parameter values and the collected 333 monthly mean $R_c$ data. The results show that the coefficient of determination...
the monthly mean could only explain 40% of the spatiotemporal variability of $K_s$ at the same site. $1$ grassland; $D$ function of SOC density. The resulting model is $R_s$ when comparing the averages of the measured and predicted capture of the variability of $K_s$ and TP2 models still existed, partly due to their insufficient capture of the variability of $R_s$ of different types of ecosystems at the same site.

Figure 2 illustrates the residual of simulated $R_{s,\text{monthly}}$. The strong correlation between the residual and SOC density suggests that SOC density was an additional factor controlling the spatial variability of $R_{s,\text{monthly}}$.

Based on the above results, we propose a new $R_s$ model (eq 5) by modifying the parameter $R_0$ in eq 4 as a linear function of SOC density. The resulting model is

$$R_{s,\text{monthly}} = (R_{D=0} + MD) e^{\alpha T}(P + P_2)/(P + K) \quad (5)$$

where $D_s$ is SOC density at a soil depth of 20 cm, $R_{D=0}$ is the $R_s$ rate when the SOC density is zero, and $M$ is parameter. The TP model has the implicit assumption of “zero-precipitation—zero-respiration”, which is actually not the scenario of natural processes. In eq 5, taking an approach similar to that by Reichstein et al. (7), we added a parameter $P_2$ to the model for taking into account the capacity of water retention in soil.

Furthermore, Zheng et al. (12) found that the spatial variability of $Q$ in China could be described by an exponential function of air temperature

$$Q = \ln \alpha e^{\beta T} \quad (6)$$

where $\alpha$ and $\beta$ are fitted parameters. By putting the eq 6 into eq 5, a new geostatistical model of soil respiration (GSMSR) can be obtained (eq 7) as follows

$$R_{s,\text{monthly}} = (R_{D=0} + MD) e^{\alpha e^{\beta T}} e^{\beta T}(P + P_2)/(K + P) \quad (7)$$

In this study, 333 $R_s$ data selected randomly from a total of 390 collected data were used for parametrization of the GSMSR model. The resulting parameters were $R_{D=0} = 0.588$, $M = 0.118$, $\alpha = 1.83$, $\beta = -0.006$, $P_2 = 2.972$, and $K = 5.657$.

2.4. Model Validation. Figure 3a and b demonstrates the ability of GSMSR to explain the variability of monthly mean $R_s$. Comparison of the measured and the simulated $R_{s,\text{monthly}}$ shows that the GSMSR model explains 64% of the seasonal variability of $R_{s,\text{monthly}}$. 58% of the variability of $R_s$ among different ecosystems at the same site, and 51% of the variability of annual $R_s$ (Figure 3c).

The GSMSR model was also validated with 57 $R_s$ data that were not used in the model parametrization. These data were measured at four forestland ecosystems (MR1 and MR2 in Maershan, QL1 and QL2 in Qilianshan), three grassland ecosystems (X4, X5, and X6 in Xilinhe), and two cropland ecosystems (S in Shenyang, AY in Anyang) (Figure 1c). The results demonstrate that the GSMSR model could well describe the seasonal dynamics of $R_s$ of different terrestrial ecosystems (Figure S2). The measured values were significantly correlated with the estimated ($R^2 = 0.68$) (Figure S3).
E. Specifically, the annual

\[
\text{R air temperature}, \quad \text{and MAP (△, mean annual precipitation)}.
\]

2.5. Boundaries of the GSMSR Parameters. The GSMSR model was driven by the spatialized environmental variables at monthly scale, and the parameters were determined empirically. If the values of environmental variables exceed the boundary condition of parameterization, the estimated result might bring discrepancy. Since SOC density at a soil depth of 20 cm in China mostly ranged from 0 to 15.09 kg m⁻², \( R \) rate was set to be unchanged if SOC density reached 15.09 kg m⁻² in this study. Monthly air temperature for model parametrization ranged from \(-15.96 \) to \( 30.96 \) °C. Therefore, we assumed that \( R \) rate was zero and the maximum when \( T \) was lower than \(-15.96 \) °C and higher than \( 30.96 \) °C, respectively.

3. Analysis of the Spatiotemporal Pattern of \( R \)

3.1. Spatial Pattern of \( R \) in China and Its Interannual Variation. Using the GSMSR model, we obtained the spatial pattern of \( R_{\text{monthly}} \) in China. The \( R_{\text{monthly}} \) values were then aggregated to the annual \( R \) rates. The mean annual \( R \) from 1995 to 2004 increased along the direction from the northwest to the southeast with the values varying from 51 to 1592 g C m⁻² yr⁻¹ (Figure S4). The annual soil CO₂ emission in China ranged from 3.77 to 4.00 Pg C yr⁻¹ during the same period, while the anomaly monthly \( R \) (the deviation from the 1995–2004 mean) varied from \(-0.646 \) to 0.035 Pg C mon⁻¹ (Figure 4a). The annual \( R \) rates in the years with abundant precipitation (e.g., 1999 and 2000), higher air temperature (e.g., 2004), or both (e.g., 1998) were obviously larger than those in other years (Figure 4a, b).

3.2. Spatial Pattern of \( R \) along Longitude and Latitude Gradients. Figure 5 shows the mean annual \( R \) along the longitude and latitude gradients at the bins of 5°. Mean annual \( R \) first decreased and then increased with increasing latitude. The highest value (i.e., \( 827 \pm 33 \) g C m⁻² yr⁻¹) occurred in latitudes ranging from 15° to 20° N. The lowest value (286 \( \pm 7 \) g C m⁻² yr⁻¹) occurred from 35° to 40° N. As the longitude increases from 70° to 135° E, the annual \( R \) increased until 110°–115° E following with a trough between 120° and 125° E. Specifically, the annual \( R \) rates stabilized at 236 \( \pm 88 \) to 249 \( \pm 105 \) g C m⁻² yr⁻¹ in the area from 70° to 90° E. An increase to the maximum of 550 \( \pm 186 \) g C m⁻² yr⁻¹ occurred from 110° to 115° E with slight decline between 120° and 125° E.

3.3. Spatial Pattern of \( R \) along the Elevation Gradient. Figure 6 illustrates that the annual \( R \) varied significantly along the elevation gradient. The annual \( R \) decreased from

585 \( \pm 154 \) to 422 \( \pm 183 \) g C m⁻² yr⁻¹ when the altitude increased from 0 to 1000 m, where the terrain was either plain or mountainous. However, the annual \( R \) increased from 365 \( \pm 152 \) to 417 \( \pm 159 \) g C m⁻² yr⁻¹ as the elevation of alpine terrain increased from 1000 to 2000 m. Similarly, the annual \( R \) rates increased from 333 \( \pm 156 \) to 426 \( \pm 158 \) g C m⁻² yr⁻¹ when the elevation on the Tibetan-Plateau terrain increased from 2000 to 4000 m. In contrast, significant decrease was observed at elevations exceeding 4000 m. For instance, the \( R \) value decreased from 318 \( \pm 138 \) to 138 \( \pm 65 \) g C m⁻² yr⁻¹ when the elevation increased from 4000 to 8000 m.

3.4. Seasonal Dynamics of \( R \) along the Latitude and Longitude Gradients. Figure 7 shows the seasonal dynamics of monthly \( R \) along the latitude and longitude gradients from 1994 to 2005. The monthly \( R \) at different latitude gradients followed the seasonal pattern of air temperature. However, the seasonal amplitude of monthly \( R \) varied with latitude. In the northern area (40° to 55° N), the seasonal amplitude of monthly \( R \) at high latitude was larger than that at low latitude mainly due to the large change in air temperature. Within the latitudes from 35° to 40° N, the seasonal amplitude of monthly \( R \) remained the smallest. Likewise, the seasonal dynamics of monthly \( R \) at different longitude gradients were in agreement with the seasonal pattern of temperature. The seasonal amplitude of \( R \) increased with increasing longitude from 70° to 135° E.

3.5. \( R \) of Different Land Cover Types. The mean annual soil CO₂ emission from 1995 to 2004 in China was 3.84 \( \pm 0.07 \) Pg C yr⁻¹. The soil CO₂ emission from cropland (22.17 \( \pm 0.18 \)% contributed most to the total emission, whereas deciduous needle-leaved forest contributed least (0.20 \( \pm 0.01 \)%, Table 1). In terms of annual soil CO₂ emission, the evergreen broad-leaved forest was the highest (698 \( \pm 11 \) g C m⁻² yr⁻¹), in contrast to the lowest from bare land (238 \( \pm 9 \) g C m⁻² yr⁻¹). The \( R \) rates of forestland were generally larger than those of cropland and grassland. The interannual \( R \) variation of deciduous needle-leaved forest was the largest (CV = 3.14%) and that of evergreen broad-leaved forest was the smallest (CV = 1.61%). The contributions of soil CO₂ emission from forestland, cropland, and grassland ecosystems to the total \( R \) in China were 48.38 \( \pm 0.35 \)%, 22.17 \( \pm 0.18 \)% and 20.83 \( \pm 0.13 \)% respectively.
3.6. Contribution of $R_s$ in China to the Global Carbon Budget. Table 2 shows the contribution of $R_s$ in China to the global carbon budget from 1995 to 2004. The $R_s$ in China accounted for 3.92%–4.78% of the global soil CO$_2$ emission, which was lower than the ratio of SOC pool in China to that of the global (5.66%–7.31%). The contributions of $R_s$ of forestland, cropland, and grassland ecosystems in China to the global total $R_s$ were 1.78%, 10.52%, and 8.49%, respectively.
TABLE 3. Comparison of Evaluation Results of $R_s$ from Different Models

<table>
<thead>
<tr>
<th>model</th>
<th>period</th>
<th>climatic data/spatial resolution</th>
<th>$R_s$ (Pg C yr$^{-1}$)</th>
<th>reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSMSR</td>
<td>1995–2004</td>
<td>interpolated from climate data of sites in China/1 km$^2$</td>
<td>3.84</td>
<td>this study</td>
</tr>
<tr>
<td>TP$^*$</td>
<td>1980–1994</td>
<td>interpolated from climate data of sites of global/0.5° × 0.5°</td>
<td>3.76</td>
<td>Raich et al. (5)</td>
</tr>
<tr>
<td>TP$^{**}$</td>
<td>1995–2004</td>
<td>interpolated from climate data of sites in China/1 km$^2$</td>
<td>3.51</td>
<td>this study</td>
</tr>
<tr>
<td>CEVSA</td>
<td>1980–2000</td>
<td>interpolated from climate data of sites in China/0.5° × 0.5°</td>
<td>4.82 (3.02$^*$)</td>
<td>Cao et al. (3)</td>
</tr>
<tr>
<td>AVIM2</td>
<td>1981–2000</td>
<td>PRECIS/50 × 50 km$^2$</td>
<td>4.43 (2.84$^{**}$)</td>
<td>Ji et al. (22)</td>
</tr>
</tbody>
</table>

$a$ China data were distilled from global data calculated by Raich et al. (5). $b$ The evaluation result of TP model (original parameters in Raich et al. (5)) with the climatic data of China. $c$ Heterotrophic respiration ($R_h$), the $R_s$ values were estimated from function: $\ln(R_h) = 1.22 + 0.73\ln(R_s)$ (21).

4. Discussion

4.1. Modification of Geostatistical $R_s$ Model. The geostatistical $R_s$ model can provide independent soil CO$_2$ emissions data for validating the process-based model (4). However, the global scale geostatistical $R_s$ model needs reparameterization or modification in structure when it is used at a regional scale because the factors determining $R_s$ vary with spatial scales.

The TP model presented by Raich et al. (5) is suitable for modeling $R_s$ at the global scale. However, the model could not well explain the variability of $R_s$ in China even if it was reparameterized with $R_s$ data in China. In this study, GSMSR was developed on the basis of TP model. The modifications include (1) the reference $R_s$ rate is expressed as a linear function of SOC density in consideration of the effect of SOC density on $R_s$ (13), (2) temperature sensitivity of $R_s$ ($Q$) is modified as an exponential function of temperature (i.e., $\ln Q = Q_{10}^T/T$) (12), and (3) a parameter $P_t$ considering soil–water regime is introduced into the model (7). GSMSR can explain 64% of the spatiotemporal variability of $R_s$ in China, much better than the behaviors of TP and TP2 models. The results suggest that the GSMSR model is suitable for evaluating the annual $R_s$ and the seasonal variability of $R_s$ of different ecosystems in China.

4.2. Comparison of $R_s$ Evaluation by Different Models. Table 3 compares the $R_s$ rates estimated by different models. The results of the GSMSR model fell within the results of other models. The mean annual $R_s$ simulated by GSMSR was 3.84 Pg C yr$^{-1}$ from 1995 to 2004. This value was slightly larger than the estimation by Raich et al. (5) and by the TP model with the climatic data in China but smaller than the results of two process-based $R_s$ models: CEVSA model (3) and AVIM2 model (22). We attribute such differences to the variations of spatial and temporal resolutions of environmental variables, modeling periods, and data used in the parametrization of models.

The GSMSR model is more accurate than other models in $R_s$ simulation and estimation, but it may have two uncertainties that need verification. First, model parametrization requires more data for cropland ecosystems than for forestland and grassland ecosystems. As a result, the model applicability may vary with ecosystem types. Second, the model might have a certain limitation in spatial representativeness because most of the sites for model validation were located in the east of China. Testing based on the measurements in other areas would help clarify the potential of spatial representativeness of the model.

4.3. Spatiotemporal Pattern of $R_s$ in China. The spatial patterns of $R_s$ variation along latitude, longitude, and elevation gradients were correlated to the spatial patterns of air temperature, vegetation types, and SOC density. Along the latitude gradient, the ecosystems in the south of China had the largest soil CO$_2$ emission due to the high temperature (Figure 5a). Temperature was low in north China, but the annual $R_s$ rates were still larger than those in central China (Figure 5a), chiefly because most ecosystems in this area at high latitudes were boreal forest ecosystems, and rich in SOC (respiration substrate) (23). The increase in $R_s$ rates with longitude (Figure 5b) was due to the low vegetation coverage in west China. In general, the decrease in $R_s$ in the area with high longitude was attributed to the land coverage by boreal and temperate forest ecosystems (Figure 5b). Temperature was the major factor controlling the temporal variation of $R_s$ at the seasonal scale. This is why the seasonal dynamics of monthly $R_s$ along latitude and longitude gradients were similar to that of temperature (Figure 7). Besides, the areas covered by forest ecosystems with high SOC density exhibited a sharp increase in soil CO$_2$ emission in summer (12). As a result, the seasonal amplitude of monthly $R_s$ in northern China was larger than that in other areas (Figure 7b). Further study is needed to distinguish the effect of longitude/latitude and elevation.

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Supporting Information Available

Additional figures. This material is available free of charge via the Internet at http://pubs.acs.org.

Literature Cited


