Global pattern of temperature sensitivity of soil heterotrophic respiration (Q_{10}) and its implications for carbon-climate feedback

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[1] Temperature sensitivity of soil respiration (Q_{10}) is an important parameter in modeling effects of global warming on ecosystem carbon release. Experimental studies of soil respiration have ubiquitously indicated that Q_{10} has high spatial heterogeneity. However, most biogeochemical models still use a globally constant Q_{10} in projecting future climate change, partly because no spatial pattern of Q_{10} values has been derived. In this study, we conducted an inverse analysis to retrieve a global pattern of spatially heterogeneous Q_{10} values by assimilating data of soil organic carbon into a process-based terrestrial carbon model (Carnegie-Ames-Stanford Approach model) at spatial resolution of 1° by 1°. The estimated Q_{10} values were, in turn, incorporated into soil respiration models to evaluate their impacts on global respiratory carbon release from soil (i.e., total soil respiration is equal to microbial and root respiration) and from microbial decomposition (i.e., heterotrophic respiration). Our results show that the optimized Q_{10} values are spatially heterogeneous and vary with environmental factors. In general, Q_{10} value tends to be high in the high-latitude regions. The mean Q_{10} values for different biomes range from 1.43 to 2.03, with the highest value in tundra and the lowest value in deserts. When spatially heterogeneous Q_{10} values were incorporated into global soil respiration models, simulated soil respiration has a feedback intensity of 3.21 Pg C °C^{-1} to climate warming, which is approximately 40% higher than that with a globally invariant Q_{10} value. The modeled heterotrophic respiration has a feedback intensity of 2.26 Pg C °C^{-1}, about 25% higher than that derived from a globally invariant Q_{10} value. Overall, the feedback intensity of soil carbon release to climate warming depends not only on the magnitude of a global mean of Q_{10} values but also their spatial variability.


1. Introduction

[2] Soil respiration in terrestrial ecosystems plays a critical role in regulating global carbon cycling. One significant factor that not only influences the response of soil respiration to global change but also determines the direction and magnitude of terrestrial carbon cycle feedback to climate warming is temperature sensitivity of soil respiration [Schimel et al., 1994; Luo, 2007]. Temperature sensitivity of soil respiration (often termed as Q_{10}) is a factor by which soil respiration is multiplied when temperature increases by 10°C [Davidson et al., 2006], which is an important parameter to evaluate the feedback intensity between soil carbon efflux and global warming [Cox et al., 2000; Luo et al., 2001; Friedlingstein et al., 2003; Reichstein et al., 2003]. So far, most models generally consider the temperature sensitivity as globally invariant when simulate global soil respiration [Friedlingstein et al., 2006]. If the spatially heterogeneity in Q_{10} is considered, the direction and magnitude of the terrestrial carbon cycle feedbacks to climate warming could be significantly changed [Jones et al., 2003]. It is an urgent need to derive the global pattern of Q_{10} and quantify its feedbacks in the terrestrial ecosystem carbon cycling to climate warming [Holland et al., 2000; Luo, 2007].

[3] There are two kinds of definitions on temperature sensitivity, i.e., “intrinsic temperature sensitivity” and “apparent temperature sensitivity” [Davidson and Janssens, 2006]. The intrinsic temperature sensitivity is the theoretic sensitivity determined by molecular structure, while the latter is the observed temperature sensitivity determined by both molecular structure and environmental constraints caused by heterogeneous soil properties [Sollins et al., 1996; Davidson and Janssens, 2006]. As environmental constrains dampen or obscure the intrinsic temperature sensitivity of substrate decomposition, the apparent (or observed) temperature sensitivity is usually less than expected value [Davidson and Janssens, 2006]. Hereafter,
the temperature sensitivity ($Q_{10}$) in this study is stated for apparent temperature sensitivity.

[4] Experimental studies of $Q_{10}$ have long and extensively been conducted in many ecosystems [Luo and Zhou, 2006]. Experimental results demonstrated that $Q_{10}$ values varied with temperature [Lloyd and Taylor, 1994; Kirschbaum, 1995; Luo et al., 2001], quantity and quality of soil organic matter [Taylor et al., 1989; Liski et al., 1999; Wan and Luo, 2003], soil moisture [Davidson et al., 1998; Reichstein et al., 2002; Hui and Luo, 2004], and land cover type [Raich and Tufekcioglu, 2000]. The $Q_{10}$ values derived from measured soil respiration and temperature usually decline with temperature because substrate availability decreases as temperature increases [see Tecler et al., 2009]. As described by the Michaelis-Menten kinetics equation, the low substrate availability generally results in a low $Q_{10}$ value [Davidson et al., 2006]. Soil water content influences temperature sensitivity because diffusivity of soluble substrates is low at low water content and diffusivity of oxygen is low at high water content. Low diffusivity of either soluble substrates at low water content or oxygen at high water content limits soil microbial respiration [Davidson et al., 2006]. All the environmental and biological factors such as soil temperature, moisture, and soil organic matter are spatially heterogeneous. Accordingly, estimated $Q_{10}$ from measured soil respiration likely varies spatially at different geographic locations [Xu and Qi, 2001].

[5] In the past, $Q_{10}$ values have been seldom estimated using process-based modeling but mostly by regression analysis of measured soil CO$_2$ efflux rates against temperature [e.g., Raich and Potter, 1995; Fang et al., 2005]. As empirical models do not contain equations to represent the underlying physical, chemical, and biological processes as described in the above paragraph, the estimated $Q_{10}$ values may not reflect true temperature sensitivity of soil respiration. High values of $Q_{10}$ estimates, such as those significantly higher than 2.5, may be caused by confounding factors, e.g., substrate supply [Davidson et al., 2006]. In addition, reliability of the estimated $Q_{10}$ values also depends on the precision of instruments used in soil CO$_2$ efflux measurement. The static chamber, for example, may underestimate soil respiration [Raich et al., 2002].

[6] Inverse modeling can be potentially a useful method to estimate temperature sensitivity of soil respiration [Raupach et al., 2005]. This method assimilates data from observations and experiments with a process-based biogeochemical model for parameter estimation. For example, Ise and Moorcroft [2006] applied an inverse modeling method to integration of a CENTURY-based mechanistic decomposition model with observed soil organic carbon content to estimate the optimal $Q_{10}$ of soil respiration. On the basis of the TECO-R model and remote sensing data, inverse modeling was also used by Zhou and Luo [2008] to estimate spatial distribution of carbon residence times for plant and soil.

[7] In this study, we used an inverse modeling approach, which assimilates a process-based model (CASA model) with the measured soil organic carbon (SOC) [Global Soil Data Task, 2000] using a constraint of the global mean $Q_{10}$ value of soil respiration reported by Raich et al. [2002] to retrieve a global distribution of spatially heterogeneous $Q_{10}$ values at a resolution of 1° × 1°. Our approach assumed that temperature sensitivity of the heterogeneous respiration ($Q_{10}$) can be constrained by the $Q_{10}$ value of soil respiration. Since the autotrophic component of soil respiration may be more sensitive than its heterotrophic component to temperature change [Boone et al., 1998], the constraint may slightly overestimate $Q_{10}$ values of the heterotrophic respiration. On the basis of the estimated $Q_{10}$ values, we analyzed the statistical dependencies of $Q_{10}$ values on environmental factors at the global scale. Finally, we used an empirical soil respiration model and a process-based model to evaluate the impacts of the spatially heterogeneous $Q_{10}$ values on respiratory carbon release from soil (i.e., total soil respiration is equal to microbial and root respiration) and microbial decomposition (i.e., heterotrophic respiration), respectively, in response to climate warming. As it is difficult to separate a $Q_{10}$ value for heterotrophic respiration and autotrophic respiration in soil at global scale, we assume the $Q_{10}$ value for heterotrophic respiration equals that for root respiration at the same spatial grid.

2. Materials and Methods

[8] Our inversion approach is based on an assumption that at equilibrium, the soil carbon input from ecosystem production and output from soil respiration is balanced. The soil carbon output by soil respiration is closely related to a $Q_{10}$ value [Xu and Qi, 2001; Fang et al., 2005]. The latter varies with climatic factors [Reichstein et al., 2003; Hui and Luo, 2004], and chemical compounds of plant litter and soil texture [Schimel et al., 1994]. Since $Q_{10}$ significantly regulates soil carbon release and then soil organic carbon (SOC) at a steady state with the yearly soil heterogeneous respiration equals ecosystem net primary production (NPP), SOC at particular geographical locations contains information on $Q_{10}$. Therefore, using the measured SOC as constraints, the optimal $Q_{10}$ can be estimated based on a rule that the deviation of the observed and modeled $Q_{10}$-related SOC is minimized.

[9] In this study, NPP and SOC were estimated using Carnegie-Ames-Stanford Approach (CASA model), which contains an ecosystem production submodel and a soil carbon submodel [Potter et al., 1993; Field et al., 1995]. The model used in this study has been improved and validated by Randerson et al. [1996], Potter and Klooster [1997], and Friedlingstein et al. [1999]. The CASA model calculates NPP as a function of normalized difference vegetation index (NDVI), photosynthetically active radiation, maximum possible light utilization efficiency, temperature and precipitation. The soil carbon submodel simulates carbon cycling using a set of compartmental difference equations based on a simplified version of the CENTURY model [Parton et al., 1987, 1988]. Carbon fluxes are controlled using nondimensional scalars related to air temperature, soil moisture, litter substrate quality (N and lignin contents), and soil texture. Carbon in soil organic form is represented by two storage pools: the SLOW pool, which chiefly contains chemically protected C, and the OLD pool, which mainly contains physically protected C. Fluxes from litter and soil to microbial pools and from microbial pools back to soil pools occur in proportion to C assimilation rates:

$$CO_2(x,t) = C(x,t) \cdot \lambda_i \cdot W(x,t) \cdot T_i(x,t) \cdot (1 - M_e)$$

(1)
where \( x \) and \( t \) represent spatial grid and time (month) respectively; \( \text{CO}_2(x, t)_i \) is production of \( \text{CO}_2 \) of pool \( i \), which results from microbe-mediated decomposition of soil organic carbon; \( C(x, t)_i \) is carbon content of pool \( i \); \( M_e \) is carbon assimilation efficiency of microbes; \( W_e(x, t) \) is scalar for the effect of soil moisture content on decomposition; \( T_e(x, t) \) is scalar for the effect of temperature on decomposition, which was treated uniformly as an exponential \( (Q_{10}) \) response:

\[
T_e(x, t) = e^{(T(x,t) - 35)/10}
\]

where \( Q_{10} \) is temperature sensitivity of soil microbial respiration and \( T(x, t) \) is monthly average air temperature.

### 2.1. Inversion Algorithm

[10] At each \( 1^\circ \) by \( 1^\circ \) spatial grid \( x \), we searched for the optimal value of \( Q_{10} \) in the domain \( Q \in [Q_{\text{min}}, Q_{\text{max}}] \) such that

\[
|S_{m,x}(Q_{10}(x)) - S_{0,x}| \leq |S_{m,x}(Q_{0}) - S_{0,x} |, \forall Q_{10} \in Q
\]

where \( S_{m,x} \) is the measured SOC at grid \( x \), which obtained directly from the SOC database [Global Soil Data Task, 2000]. \( S_{m,x}(Q_{10}(x)) \) is CASA modeled SOC with the optimal \( Q_{10} \) value \( (Q_{10}^{*}) \), which is related with the searching domain \( Q \). \( S_{m,x}(Q_{10})(x) \) is modeled SOC with an arbitrary \( Q_{10} \) value \( (Q_{10}) \) that locates in the domain \( Q \). After the optimal \( Q_{10} \) values for all grids are estimated, the modeled global mean SOC in the domain \( Q \) has the minimal deviation with the global mean observations:

\[
J(Q) = \sum |S_{m,x}(Q_{10}(x)) - S_{0,x}| \times a(x)
\]

where \( a(x) \) is grid area of \( x \), and \( J \) is the global mean deviation between modeled and observed SOC, which depends on the optimal \( Q_{10} \) value of each grid and therefore related with the searching domain \( Q \).

[11] The reasonable low limit \( (Q_{\text{min}}) \) of domain \( Q \) is relatively easy to assign. In this study \( Q_{\text{min}} \) equals 1, which means that soil respiration do not change with temperature; it usually appears at soil type of entisol where SOC is absent. The reasonable upper limit \( (Q_{\text{max}}) \), however, is somewhat difficult to define as the estimated upper limits from soil respiration measurements can be very high (e.g., significantly above 2.5), which probably can be attributed to some confounding effects from substrate supply and other processes [Davidson et al., 2006].

[12] For this reason, we did not prescribe a prior \( Q_{\text{max}} \) value. Rather, we constrained the \( Q_{\text{max}} \) value according to the following considerations. The global mean \( Q_{10} \) value \( (Q_{10}) \) has been estimated from worldwide soil respiration measurements [Raich and Potter, 1995; Raich et al., 2002]. Our globally averaged \( Q_{10} \) value should be matched with this value derived from the measurements of soil respiration:

\[
Q_g(Q_{\text{max}}) = \sum_{x} \frac{[a(x) \times Q_{g}(x)]}{\sum_{x} a(x)}
\]

where \( Q_g \) is the global mean \( Q_{10} \) value that related with optimal \( Q_{10} \) values of grids and therefore, related with the upper limit of domain \( (Q_{\text{max}}) \). The value of \( Q_{10} \) used in this study equals 1.72 as reported by Raich et al. [2002] from soil respiration measurements in major ecosystems of the world.

### 2.2. Data

[13] The spatial data sets used in this study include (1) vegetation type, soil texture, multiyear monthly mean AVHRR-NDVI and solar radiation (provided by Climatology Interdisciplinary Data Collection and issued by Distributed Active Archive Center at Goddard Space Flight Center, http://daac.gsfc.nasa.gov); (2) multiyear monthly mean temperature and precipitation data sets (provided by C. J. Willmott and K. Matsuara, http://climate.geog.udel.edu/~climate); and (3) the maps of soil organic carbon and nitrogen (provided by IGBP-DIS [Global Soil Data Task, 2000]). All of those global data sets were resampled to the same geographic projection and at spatial resolution of \( 1^\circ \) by \( 1^\circ \) in ERDAS IMAGINE 8.5.

[14] The observations of soil respiration used for verification came from the literature and compiled by Raich et al. [2002] and have been used to verify the Raich’s soil respiration model. All of those soil respiration measurements were made with dynamic chambers coupled to infrared gas analyzers (IRGA).

### 2.3. Verification

[15] To verify if the spatial pattern of estimated \( Q_{10} \) values from the inversion algorithm is reasonable, we estimated soil respiration at several representative sites and compared them to the field measurements. As the spatially heterogeneous \( Q_{10} \) values were estimated from assimilation of the spatial pattern of observed SOC into the CASA model and further constraints by the global mean \( Q_{10} \) over worldwide soil respiration measurements, it was expected that the estimated \( Q_{10} \) values could improve fitness of modeled soil respiration to the measured one in comparison to that with the invariant \( Q_{10} \) in different spatial grids. To do so, we applied a statistic of root-mean squared errors (RMSE) to evaluate its improvement of modeled soil respiration using the spatially heterogeneous \( Q_{10} \) values estimated from this inverse analysis relative to those using a globally invariant \( Q_{10} \) in different spatial grids.

### 2.4. Evaluations of Spatial Patterns of \( Q_{10} \) on Modeling of Soil Respiration

[16] To evaluate the potential influences of spatially heterogeneous \( Q_{10} \) values on soil respiration modeling, we used an empirical soil respiration model as in the work of
Raich et al. [2002] to simulate soil respiration (i.e., both soil heterotrophic respiration and root respiration), which is matched with field soil respiration measurements. In addition, we used a process-based model, the CASA soil carbon submodel, to simulate soil heterotrophic respiration, which accounts for simultaneous changes in soil C stocks and temperature sensitivity of soil respiration.

[17] The original Raich’s model uses a global invariant $Q_{10}$ value ($Q_{10} = 1.72$) and expresses as:

$$Model\ A: R_s = \frac{F}{C_2} e^{b x T_a} \times \frac{P}{(K + P)}$$  

where $R_s$ refers to the mean monthly soil respiration in g C m$^{-2}$ d$^{-1}$; $b$ is a constant temperature sensitivity ($b = \frac{\ln Q_{10}}{10} = 0.054$); $T_a$ refers to the mean monthly air temperature ($^\circ$C), and $P$ is the mean monthly precipitation (cm); $F$ and $K$ are constants ($F = 1.250$ and $K = 4.259$) derived from the observed soil respiration.

[18] The modified model uses the inverted global pattern of $Q_{10}$ values and expresses as:

$$Model\ B: R'_s = F \times e^{(b_x \times T_a)} \times \frac{P}{(K + P)}$$  

where $b_x$ is our estimated temperature sensitivity at spatial grid $x$ ($b_x = \frac{\ln Q_{10}(x)}{10}$); $R'_s$ refers to the mean monthly soil respiration with spatially heterogeneous $Q_{10}$ values in g C m$^{-2}$ d$^{-1}$.

[19] We selected Raich’s model because it is developed upon the worldwide measurements of soil respiration. In addition, the global mean value of our inverted $Q_{10}$ is the same with the Raich’s global invariant $Q_{10}$ value (i.e., $Q_{10} = 1.72$), so the deviation of total modeled soil respiration is completely induced by the spatial distribution of $Q_{10}$ values.

[20] We also evaluated potential impacts of spatially heterogeneous $Q_{10}$ on carbon cycle–climate change feedback via soil respiration under two scenarios. The first one is a $1^\circ$C increase of temperature evenly in each spatial grid. The second one is the actual interannual variations of temperature observed from 1982 to 1999 [Legates and Willmott, 1990a, 1990b]. In both scenarios, soil respiration was modeled simultaneously by empirical models A and B, while the soil heterotrophic respiration was modeled by CASA soil carbon submodel, in which the spatially heterogeneous and the globally invariant $Q_{10}$ were both used.

3. Results

3.1. Global Pattern of $Q_{10}$

[21] At the global scale, the optimal mean $Q_{10}$ value increases but the mean deviation between the modeled and observed SOC decreases with the upper limit of domain Q (i.e., $Q_{\text{max}}$) (Figure 1). As $Q_{\text{max}}$ becomes larger, there are

Figure 1. Relationship between optimal global mean $Q_{10}$ value and upper limit of domain Q. As $Q_{\text{max}}$ becomes larger, there are more chances to find a better $Q_{10}$ by the inverse algorithm to minimize the deviation of the modeled SOC from the observed one. However, the rate of this improvement of the model-data match declines to be sufficiently small as $Q_{\text{max}}$ becomes higher than 2.61, at which value the globally mean $Q_{10}$ value ($\overline{Q}_{10}$) that derived from worldwide measurements of soil respirations is 1.72.

Figure 2. Spatial pattern of the optimal $Q_{10}$ values. In general, tundra, C3 and C4 grasslands, shrublands, and croplands have higher $Q_{10}$ values than deserts, bare grounds, broadleaf deciduous forests, and woodlands.
more chances to find a better $Q_{10}$ by the inverse algorithm to minimize the deviation of the modeled SOC from the observed one in any particular spatial grid. However, the rate of this improvement of the model-data match declines to be sufficiently small as $Q_{\text{max}}$ becomes higher than 2.61, at which the globally mean $Q_{10}$ value ($\bar{Q}_{10}$) is 1.72. The latter was derived from worldwide measurements of soil respirations. Thus, the globally mean $Q_{10}$ value of 1.72 is an effective constraint in our inverse analysis to retrieve optimal $Q_{10}$ values from observed SOC in individual spatial grids. It also suggests that the $Q_{10}$ values derived from measured soil respiration are, on average, consistent with those estimated from our inverse analysis that assimilated observed SOC into a process-based carbon cycle model.

[22] The derived spatial pattern of the optimal $Q_{10}$ values at global scale shows a great spatial heterogeneity (Figure 2). The optimal $Q_{10}$ values for each biome range from the lowest of 1.43 for desert and bare ground to the highest of 2.03 for tundra (Table 1). In general, tundra, C3 and C4 grasslands, shrublands, and croplands have higher $Q_{10}$ values than deserts, bare grounds, broadleaf deciduous forests, and woodlands. The optimal $Q_{10}$ values are relatively higher in the higher-latitude regions as reflected by a positive correlation between latitudes ($^\circ$) and the latitudinal mean $Q_{10}$ values ($r = 0.51$).

### 3.2. Comparison of Modeled With Observed Soil Respiration

[25] Incorporation of site-specific $Q_{10}$ values into the model B (equation (8)) consistently improved simulated soil respiration in comparison with those with the invariant $Q_{10}$ in model A (equation (7)) at all sites (Figure 3). The root-mean squared errors (RMSE) between the modeled and observed soil respiration decrease by 3.1 to 30.0% for different sites with the site-specific $Q_{10}$ values than the globally invariant $Q_{10}$ values. For instance, RMSE of a deciduous forest in USA (43.1°N, 70.0°W) is 0.61 when using our estimated $Q_{10}$ of 1.80, while the corresponding RMSE is 0.73 when using a constant $Q_{10}$ of 1.72. Thus, the RMSE decreased by 16.4%.

### 3.3. Statistical Dependency of $Q_{10}$ on Environmental Factors

[24] Correlation analysis indicates that the $Q_{10}$ values estimated by our inverse method are statistically related with environmental factors such as soil organic carbon content and mean annual precipitation (MAP). $Q_{10}$ values are positively correlated with soil organic carbon and soil nitrogen contents, with the correlation coefficients of 0.30 and 0.31, respectively (Table 2). The correlation between $Q_{10}$ and MAP is positive for the broadleaf evergreen forests, broadleaf deciduous forests, grassland, cultivation, and desert and bare ground but negative for needleleaf forests and high-latitude deciduous forest.

### 3.4. Impacts of $Q_{10}$ on Global Soil Respiration Modeling

[25] Under the first scenario with an even increase in temperature by 1°C for each spatial grid, simulated soil respiration by the empirical model A with globally invariant $Q_{10}$ is considerably different from that by the model B with spatially heterogeneous $Q_{10}$ (Figures 4a and 4b). The relative discrepancy between the two models is larger than ±5% (Figure 4b). The absolute discrepancy of the simulated soil respiration between the two models is largest in the latitude band of 0°–30°N and quite minor in the latitude bands of 60°–90°N and 30°–60°S. At the global scale, the increment of modeled soil respiration with the spatially heterogeneous $Q_{10}$ values is 7.02 Pg C a⁻¹ in response to climate warming by 1°C, which is much higher than 4.16 Pg C a⁻¹ estimated with an globally invariant $Q_{10}$ value. Thus, the feedback intensity between soil respiration and climate warming would be underestimated by 40.7% if the spatially heterogeneous $Q_{10}$ values were not considered.

[26] Under the first scenario, soil heterotrophic respiration simulated by the CASA soil carbon submodule displays a similar spatial pattern of relative discrepancy between the spatially heterogeneous and invariant $Q_{10}$ (Figure 4d), but the absolute discrepancy between the two types of $Q_{10}$ in simulated heterotrophic respiration by the CASA model is apparently less than total respiration by the empirical models (Figure 4a versus Figure 4c).
Under the second scenario with the actual observed interannual variation of temperature from 1982 to 1999, the temperature anomaly (i.e., the departure of the mean annual temperature from the total mean) ranged from \(-0.40\) to 0.47. In correspondence, the anomaly of modeled soil respiration (i.e., the departure of modeled soil respiration in a particular year from the total mean during the period) ranges from \(1.01\) to \(1.44\) Pg C a\(^{-1}\) for the globally invariant \(Q_{10}\) value in model A and from \(-1.79\) to \(2.96\) Pg C a\(^{-1}\) for spatially heterogeneous \(Q_{10}\) values in model B (Figure 5a). The linear regression between the anomaly of global mean annual temperature and the anomaly of modeled soil respiration has a slope of \(1.88\) Pg C°C\(^{-1}\) for the globally invariant \(Q_{10}\) and \(3.21\) Pg C°C\(^{-1}\) for the spatially heterogeneous \(Q_{10}\) values (Figure 5a). Although the temperature sensitivity of soil respiration estimated according to temperature anomaly under scenario 2 is less than that estimated under scenario 1 in the absolute magnitude, the relative magnitude of underestimation of the sensitivity by the globally invariant \(Q_{10}\) in comparison to that by the spatially heterogeneous \(Q_{10}\) is 41.4%, similar to that under scenario 1 (40.7%).

Under scenario 2, soil heterotrophic respiration simulated by the CASA model has the temperature sensitivity of \(2.26\) Pg C°C\(^{-1}\) when the spatially heterogeneous \(Q_{10}\) was considered (Figure 5b). As a comparison, the corresponding sensitivity is \(1.69\) Pg C°C\(^{-1}\) (Figure 5b) with the globally invariant \(Q_{10}\).

4. Discussion
4.1. Influences of Constraints on Estimation of Spatial Pattern of \(Q_{10}\)

In this inverse analysis, we used spatially distributed measurements of soil organic carbon and several ancillary variables to constrain a process-based biogeochemical
models to extract information on temperature sensitivity of soil heterotrophic respiration. We also used the global mean of the experimentally derived Q_{10} as a further constraint on estimation of the temperature sensitivity. Soil organic carbon originates from plant production and litter input. It accumulates slowly in soil to a steady state if there is no disturbance [Li et al., 2004]. Therefore, the Q_{10} values derived from the observed soil organic carbon and relevant environmental factors are multiyear averaged temperature sensitivity, which is somewhat different from those derived from instantaneous measurements of soil respiration. The derived Q_{10} values from this inverse analysis are more suitable for projecting long-term climate-carbon cycle feedback at large spatial scales.

Experimentally derived Q_{10} values from instantaneous soil respiration measurements reflect apparent temperature sensitivity at local scales and vary with many site-specific conditions [Davidson and Janssens, 2006]. The site-specific Q_{10} values cannot be easily scaled up to analysis at regional or global scales for at least two reasons. First, observations of soil respiration are too sparse and the ecosystems are too heterogeneous to allow large-scale assessment with sufficient accuracy [Denman et al., 2007]. Second, experiment-based Q_{10} values are usually derived from regression analysis and can be unreasonably high or low due to confounding factors [Davidson et al., 2006]. To avoid these issues, we used the global mean Q_{10} value as a constraint instead of the site-specific Q_{10} values.

The inversion approach searched for optimal Q_{10} values by minimizing differences between modeled and observed SOC contents. The estimated Q_{10} values can be influenced by the inverse method, the model used in the analysis, and the searching range of Q_{10} values. When the experiment-based global mean Q_{10} value (= 1.72) was used as a constraint in the inverse analysis, the upper limit of Q_{max} equals 2.61 (Figure 1), which is amazingly similar to the value of 2.5 purely based on a theoretic analysis [Davidson et al., 2006]. In addition, site-specific Q_{10} values

### Table 2. Correlations Between Q_{10} and Soil Organic Carbon and Nitrogen Content

<table>
<thead>
<tr>
<th>Land Cover Type</th>
<th>Q_{10} and SOC</th>
<th>Q_{10} and N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Broadleaf evergreen forest</td>
<td>0.56&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.58&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Broadleaf deciduous forest</td>
<td>0.28&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.32&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Mixed forest and woodland</td>
<td>0.39&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.42&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Coniferous forest and woodland</td>
<td>0.67&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.57&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>High-latitude deciduous forest and woodland</td>
<td>0.84&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.78&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Woody C_4 grassland</td>
<td>0.48&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.45&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>C_4 grassland</td>
<td>0.38&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.38&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Shrubs</td>
<td>0.11&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.28&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Tundra</td>
<td>0.41&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.34&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Desert, bare ground</td>
<td>0.23&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.19&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>Cultivation</td>
<td>0.22&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.24&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>C_3 wooded grassland</td>
<td>0.39&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.42&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>C_4 grassland</td>
<td>0.26&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.28&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
<tr>
<td>All vegetation</td>
<td>0.30&lt;sup&gt;b&lt;/sup&gt;</td>
<td>0.31&lt;sup&gt;b&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

<sup>a</sup>SOC, soil organic carbon; N, nitrogen.
<sup>b</sup>Correlation is significant at the 0.01 level.

Figure 4. Absolute and relative discrepancies for total soil respiration and heterotrophic respiration increments modeled by the empirical and the process-based model at the scenario that temperature in each grid evenly increases 1°C. Absolute discrepancies for (a) total respiration and (c) heterotrophic respiration (modeled values of global invariant Q_{10} minus modeled value of spatial pattern of Q_{10}). Corresponding relative discrepancies for (b) total respiration and (d) heterotrophic respiration.
4.2. Spatially Variable Q10 Values and Their Impacts on Carbon Cycle–Climate Change Coupling

One urgent mission in the Earth system science is to couple climate models with biosphere models to examine climate change–carbon cycle feedback [Solomon et al., 2007]. However, the spatial resolution of climate system models is usually much larger than those of Q10 values derived from soil respiration measurements. As a consequence, newly derived Q10 values from ecological research could not be timely incorporated into the climate system models to improve our prediction of climate change. For example, it has been extensively illustrated by ecologists that Q10 values are spatially heterogeneous. The coupled models of a climate system with terrestrial carbon cycling, however, still use an assumed, globally invariant Q10 value [Luo, 2007]. The main cause is that ecosystems are too heterogeneous to allow a global assessment with sufficient accuracy [Denman et al., 2007]. In this study we retrieved a spatial pattern of heterogeneous Q10 values at the 1° by 1° resolution based upon two considerations. First, the global data sets at 1° by 1° are plenteous for inversion algorithm. Second, this spatial resolution is matched with the general atmospheric circulation models (GCMs) and therefore useful for research on the climate-carbon feedback.

The feedback intensity of global warming and soil carbon release depends not only on the magnitude of a global mean Q10 value but also their spatial variability. Our analysis on interannual variability in soil respiration caused by temperature anomaly indicates that the feedback intensity of total soil respiration and heterotrophic respiration to climate warming is 1.88 Pg C °C⁻¹ and 1.69 Pg C °C⁻¹, respectively, when a global invariant Q10 value was used. When spatially heterogeneous Q10 values were incorporated into models, the feedback intensity of total soil respiration and heterotrophic respiration is 3.21 Pg C °C⁻¹ and 2.26 Pg C °C⁻¹, respectively. Thus, a coupled climate-carbon cycle model that ignores spatial heterogeneity of Q10 would underestimate soil respiration by approximately 40% and heterotrophic respiration by about 25%.

5. Conclusions

Temperature sensitivity of soil respiration (as indicated by Q10) and its spatial variability are crucial for projecting climate change and atmospheric CO₂ concentration in the future. Our inverse analysis show that the observed soil organic carbon content and soil respiration offer good constraints on estimation of Q10 values in different spatial grids. Estimated Q10 values have a high spatial heterogeneity and are regulated by many spatially heterogeneous environmental factors. Q10 values vary with biome types and, in general, are higher at high-latitude bands. The derived spatially heterogeneous Q10 values result in better soil respiration estimation at different sites than the globally invariant Q10. The feedback intensity of total soil respiration and heterotrophic respiration to climate warming would be underestimated by about 40% and 25%, respectively, if a globally invariant Q10 rather than spatially heterogeneous Q10 values are used in models.

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References


Savage, K., T. R. Moore, and P. M. Crill (1997), Methane and carbon dioxide exchanges between the forest and northern boreal forest ecosystems, *Ecosystems, 1*, 29–79.


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