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RESEARCH ARTICLE

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Estimation of soil organic carbon based on remote sensing and process model

Abstract The estimation of the soil organic carbon content (SOC) is one of the important issues in the research of the global carbon cycle. However, there are great differences among different scientists regarding the estimated magnitude of SOC. There are two commonly used methods for the estimation of SOC, with each method having both advantages and disadvantages. One method is the so called direct method, which is based on the samples of measured SOC and maps of soil or vegetation types. The other method is the so called indirect method, which is based on the ecosystem process model of the carbon cycle. The disadvantage of the direct method is that it mainly discloses the difference of the SOC among different soil or vegetation types. It can hardly distinguish the difference of the SOC in the same type of soil or vegetation. The indirect method, a process-based method, is based on the mechanics of carbon transfer in the ecosystem and can potentially improve the spatial resolution of the SOC estimation if the input variables have a high spatial resolution. However, due to the complexity of the process-based model, the model usually simplifies some key model parameters that have spatial heterogeneity with constants. This simplification will produce a great deal of uncertainties in the estimation of the SOC, especially on the spatial precision. In this paper, we combined the process-based model (CASA model) with the measured SOC, in which the remote sensing data (AVHRR NDIV) was incorporated into the model to enhance the spatial resolution. To model the soil base respiration, the Van't Hoff model was used to combine with the CASA model. The results show that this method could significantly improve the spatial precision (8 km spatial resolution). The results also show that there is a relationship between soil base respiration and the SOC as the influence of environmental factors, i.e., temperature and moisture, had been removed from soil respiration which makes the SOC the most important factor of soil base respiration. The statistical model of soil base respiration and the SOC shows that the determinant coefficient (R^2) is 0.78. As the method in this paper contains advantages from both direct and indirect methods, it could significantly improve the spatial resolution and, at the same time, keep the estimation of SOC well matched with the measured SOC.

Keywords soil organic carbon (SOC), soil base respiration, remote sensing, process-based model, China

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1 Introduction

The intensity of global warming in the future is highly related with the soil carbon cycle (Prentice, 2001). The storage and spatial distribution of soil organic carbon (SOC) largely impact soil base respiration and, therefore, magnify or minimizes the feedback intensity between global warming and soil carbon release (Zhou et al., 2004). As the largest organic carbon pool in the terrestrial ecosystem (Post et al., 1990; Lal, 2002), SOC research has gained more and more attention, especially in China (Jin et al., 2001; Li and Zhao, 2001; Wu et al., 2003; Wang et al., 2003). Nevertheless, there are still a lot of uncertainties on SOC content for its high spatial heterogeneity (Palmer et al., 2002).

There are two commonly used methods for the estimation of SOC content (Post et al., 2001). One is the so called direct method, which is based on the sample of measured SOC and soil or vegetation map. The other one is the so called indirect method, which is based on the process model of the terrestrial carbon cycle. Although the estimated total storage of SOC by the direct method is similar (Kern, 1994), there are a lot of uncertainties on the SOC's spatial distribution because the direct method can hardly distinguish the spatial difference within same type of soil or vegetation. The research on observed SOC, however, indicates that the difference of the same soil type is high (Wang et al., 2003; Zhou et al., 2003). Therefore, it is necessary to use more observations to improve the precision of spatial distribution (Li et al., 2001; Wang et al., 2003).

The indirect method is based on process models of the carbon cycle and is widely used in regional SOC estimation (Post et al., 2001). As the process-based models, such as the CENTURY model (Parton et al., 1995) and CASA model (Potter et al., 1993), describe dynamic change of SOC, they have some irreplaceable advantages in SOC estimation. The indirect method has also been used to estimate SOC in China. For instance, Li et al. (2003) applied the CEVSA model to estimate the spatial distribution of soil organic carbon content in 0.5 degree resolution. However, due to the limitation of knowledge and data, the model usually simplifies some key parameters and, therefore, introduces a great deal of uncertainties on the SOC estimation.

As a modern technology with high spatio-temporal resolution, remote sensing provides a lot of useful information on soil survey and biosphere dynamic change (Post et al., 2001). Unfortunately, the spatial distribution of the SOC content cannot be directly detected by remote sensing data. Instead, the SOC estimated by remote sensing usually introduces some substituted index (Merry and Levine, 1995). That means that the simplest remote sensing data has difficulty improving the precision of the SOC estimation.

Considering the advantages and disadvantages of the different methods on regional SOC estimation, we developed an integrated method that combines the direct method with the indirect one to estimate the spatial distribution of SOC in China. As the remote sensing data of NDVI is widely used in the estimation of spatial distribution of terrestrial NPP in China (Sun and Zhu, 2000; Piao et al., 2001; Yu et al., 2001; Fang et al., 2003), and as the CASA model has been successfully applied in China (Piao et al., 2001; Fang et al., 2003), we, firstly, applied the CASA model to retrieve the spatial pattern of soil base respiration. After that, we built a statistical relationship between the retrieved soil base respiration and the observation of soil organic carbon (National Soil Survey Office, 1998; National Soil Survey Office, 1995; Wang et al., 2001a). Finally, we estimated the SOC's spatial distribution of 8 km spatial resolution from the retrieved soil base respiration.

2 Research region and data

Soil types in China present obvious zonality, i.e. latitudinal zonality controlled by difference of latitudinal temperature and longitudinal zonality controlled by difference of longitudinal precipitation. In this study, we focus our research region in all zonal soil types (Fig. 1). They include (Zhao and Gong, 1991): (1) latitudinal zonality soils, i.e., latosols → latosolic red soils → red soils → yellow soils → yellow brown soils → brown soils → dark-brown soils; (2) longitudinal zonality soils in temperate climate zone: dark-brown soils → black soils → chernozems → castanozems → brown caliche soils → gray desert soils → gray-brown desert soils; (3) longitudinal zonality soils in warm temperate climate zone: brown soils → cinnamon soils → dark loessial soils → sierozems → brown desert soils.

We focus our research region on these zonal soil types because they are widely distributed in China and at the same time they are mainly impacted by zonal climate factors, especially zonal temperature and precipitation factors. In addition, the impact of human activities on these soil types is relatively small.

The data used for estimating the spatial distribution of soil organic carbon include monthly AVHRR NDVI in 8 km spatial resolution, 1:4000000 maps of soil type and vegetation type, 1: 1400000000 map of soil texture, the measured SOC data originated from the second soil survey of China, averaged monthly temperature and precipitation data of 726 meteorologic sites, and solar radiation observation of 120 meteorologic sites.

3 Methods

3.1 Soil base respiration

The SOC is an extremely important carbon pool in the terrestrial ecosystem. Atmospheric CO_2 enters the ecosystem through plant photosynthesis and forms the organic carbon of vegetation. After that, the organic carbon enters the soil in the form of litter. Some carbon in litter is released to the atmosphere through heterotrophic respiration and some become soil humus through a humidification process. The carbon in soil humus is further decomposed by microbes and released into atmosphere (Zhou et al., 2002). The magnitude and change of SOC is determined by soil carbon input and output, which are related with ambient environmental factors. Ignoring the disturbance factors, for instance fire, the magnitude of SOC was controlled by climatic factors and it would gradually achieve a dynamic balance state during the soil's long-term evolution. That is, the soil carbon's input through litter-fall equals the soil carbon's output through heterotrophic respiration. As SOC is the raw material of

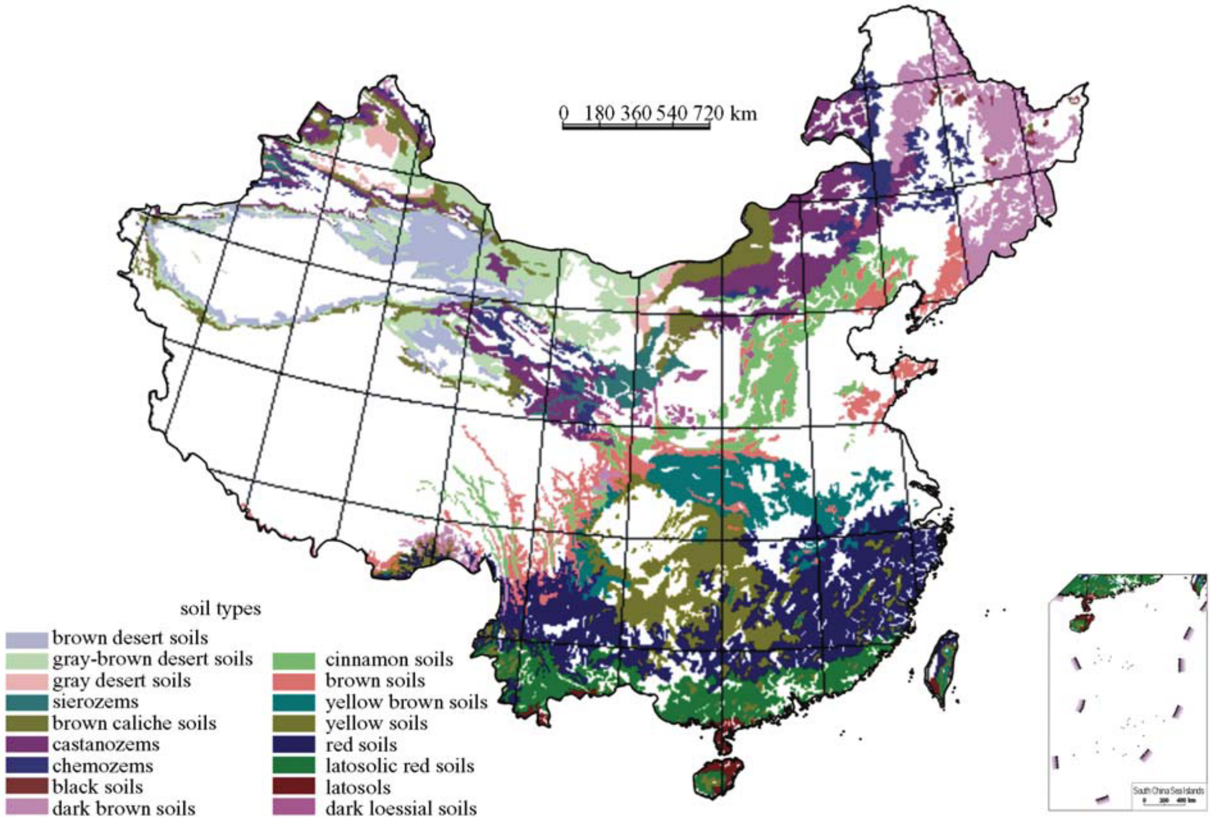

Fig. 1 Distribution of typical soils in China

soil respiration, so the quantity and quality of SOC directly affects soil respiration intensity (Hogberg et al., 2001). Considering that the spatial distribution of an ecosystem's net primary production (NPP) estimated by remote sensing data and light-use efficiency model has improved greatly (Potter et al., 1993; Prince and Goward, 1995; Ruimy and Saugier, 1994; Field et al., 1995; Sun and Zhu, 2000; Piao et al., 2001), it is a good method to retrieve the SOC-related soil respiration from the remote sensing-based process model.

However, although the SOC content is related to soil respiration, it is hardly estimated directly from soil respiration because soil respiration is controlled by many environmental factors. The SOC content is not the only factor that impacts soil respiration. Climatic factors and soil physical or chemical properties impact soil respiration, as well (Fang et al., 1998). For instance, temperature significantly impacts soil respiration intensity (Fang et al., 1998; Raich et al., 2002; Reichstein et al., 2003) and precipitation also significantly impacts soil respiration in arid and semi-arid regions. From the viewpoint of large scales, temperature is a more important influencing factor than the SOC content on soil respiration. For example, although high-latitudinal forest soils have higher SOC, the actual soil respiration for these regions are relatively low (Zhou et al., 2004) due to the low temperature. Therefore, if soil respiration was used to estimate the SOC content, it is necessary to exclude effects of climatic factors (i.e. temperature and precipitation).

Soil base respiration is soil respiration when soil temperature equals 0°C and there is no water stress (Luo et al., 2001). It is better than actual soil respiration on SOC estimation. Because the climatic factors are the same for soil base respiration, the magnitude of the SOC becomes the most important factor on soil base respiration. Despite that, soil base respiration is a better index on SOC estimation, but the values of soil base respiration are quite scarce. As a result, it is necessary to combine remote sense data and the carbon cycle process model to retrieve soil base respiration first, and then to estimate spatial pattern of SOC based on the relationship between SOC and soil base respiration.

3.2 Retrieval of soil base respiration

Based on the carbon transfer mechanism among vegetation, litter, and soil carbon pools, the dynamic of carbon in biomass, litter, and soil can be represented by following equations:

$$\frac{\mathrm{d}B}{\mathrm{d}t} = NPP - f_{BL} \tag{1}$$

where B is biomass carbon (g/m^{2}); f_{BL} is litterfall rate (g/(m^2·yr)); NPP is net primary production (g/(m^2·yr)), which can be calculated from CASA model by using $NDVI$, photosynthetically active radiation (PAR), maximum potential light-use efficiency (ε^*), and temperature $g(T)$ and soil moisture function $h(w)$ (Potter et al., 1993; Field et al., 1995):

$$NPP = PAR \times f(NDVI) \times \varepsilon^* \times g(T) \times h(w) \tag{2}$$

In this study, solar radiation data was provided by the Chinese Meteorological Data Sharing Service System. They are converted to PAR by multiplying coefficient of 0.5. The ratio of vegetation intercepted PAR is a function of $NDVI$ (Potter et al., 1993) and $PAR \times f(NDVI)$ in formula (2) equals absorbed photosynthetically active radiation ($APAR$). The estimated NPP depends on a key parameter of light-use efficiency (ε). As ε is dependent on potentially maximal light-use efficiency (ε^*) and temperature and moisture's scalars, it can be calculated by the formula $\varepsilon = \varepsilon^* \times g(T) \times h(W)$. ε^* depends on vegetation types and it is a constant for a certain vegetation. In short, NPP in this study is calculated by the CASA model based on remote sensing data ($NDVI$), meteorological data, and other auxiliary GIS data (e.g. soil texture and map of vegetation type).

Litterfall rate f_{BL} is linearly related with biomass B (King et al., 1997) while the coefficient of litterfall depends on vegetation type:

$$f_{BL} = k_{BL} \times B \tag{3}$$

The change of the litter carbon pool depends on litterfall rate and the corresponding mineralization rate:

$$\frac{dL}{dt} = f_{BL} - f_{Lh} - R_L \tag{4}$$

where L is the carbon pool of litter; f_{Lh} and R_L are the humification and mineralization rates, respectively, which are functions of temperature (T) and soil moisture (β) (Wang et al., 2001b; Zhou et al., 2002) and can be expressed as:

$$f_{Lh} = \sigma_1 \times f_1(T) \times f_2(\beta) \times L \tag{5}$$

$$R_L = \sigma_2 \times f_1'(T) \times f_2'(\beta) \times L \tag{6}$$

where $f_1(T)$ and $f_1'(T)$ are influences of temperature; $f_2(\beta)$ and $f_2'(\beta)$ are influences of soil moisture. As the litter's humification and mineralization are controlled by microbes, the impacting intensity of microbe on a certain site's humification and mineralization are the same (i.e., $f_1(T) = f_1'(T)$, $f_2(\beta) = f_2'(\beta)$); the coefficients of σ_1 and σ_2 are humification and mineralization rate which depend on vegetation types:

$$\frac{\sigma_2}{\sigma_1 + \sigma_2} = K_v \tag{7}$$

where K_v is the fraction of litter mineralization, which is a constant for the same vegetation type. The value of K_v range from 0.65 for tropical rainforest and monsoon forest to 0.75 for tropical desert and semi-desert biomes, but most of vegetation has the value of 0.70 (Foley, 1995). The change of soil humus depends on the humification rate and humus decomposition rate:

$$\frac{dS}{dt} = f_{Lh} - R_h \tag{8}$$

where R_h is humus decomposition rate. When an ecosystem's carbon cycles are in equilibrium state, the plant fixed organic carbon (NPP) is equal to the ecosystem heterotrophic respiration (R_H):

$$NPP \times (1 - K_v) = R_h \tag{9a}$$

$$NPP \times K_v = R_L \tag{9b}$$

$$NPP = R_H \tag{9c}$$

Considering the potential impact of soil moisture on heterotrophic respiration in arid or semi-arid regions, we referred to the Century model (Parton et al., 1992) and used the following improved soil respiration model:

$$R_H = a_{ij} \times e^{(b \times T)} \times y \tag{10}$$

$$y = \frac{1}{1 + 30.0 \times e^{-8.5 \times x}} \tag{11}$$

$$x = \frac{PPT}{PET} \tag{12}$$

where a_{ij} is soil base respiration; PPT is annual precipitation and PET is annual potential evapotranspiration; y is the scalar of soil moisture on soil respiration (Parton et al., 1992), which ranges from 0.03 to 1. When precipitation equals potential evapotranspiration (i.e., $y \approx 1$), soil moisture has no stress on soil respiration; when precipitation is less than potential evapotranspiration (i.e., $y < 1$), soil respiration is related to temperature and precipitation.

At the equilibrium state, soil base respiration (a_{ij}) can be estimated by formula (13).

$$a_{ij} = \frac{NPP}{e^{(b \times T)} \times y} \tag{13}$$

3.3 Flow chart of soil organic carbon estimation

Considering the interannual fluctuation of NDVI and climatic factors, we use the multi-years' averaged values from 1982 to 1999 as the CASA model's input data. The steps for soil organic carbon estimation are (Fig. 2):

1) Selecting NDVI data of China from the global NDVI data sets and transforming it to an Albers projection in Arc/Info software.

2) Digitizing the Soil Texture Map of China and matching it with NDVI data; transforming latitudes and longitudes of meteorologic sites to coordinates of an Albers projection and then interpolating them by the Kriging method in Arc/Info to gain 8 km resolution maps.

3) Estimating the spatial distribution of NPP by the CASA model (Potter et al., 1993; Potter and Klooster, 1997).

4) Estimating the spatial distribution of soil base respiration (a_{ij}) by an ecosystem carbon balance model.

5) Building the statistical relationship between the estimated soil base respiration and the observations of SOC originating from the second national soil survey (Wang et al., 2001b; Zhou et al., 2003), and finally estimating the spatial distribution of SOC in 8 km resolution.

4 Results

The results indicate that the estimated soil base respiration (a_{ij}) has a good relationship with the observed soil organic carbon content (Table 1, Figs. 3 and 4). This good relationship is because that soil base respiration is a climatic factors-independent index. Soil properties (e.g. SOC content) become the dominant factor for soil base respiration. The regressive coefficient of determination (R^2) between the soil base respiration and the observed SOC is 0.78.

As the direct method of SOC estimation is based on the soil sample (e.g. Wang et al., 2001b), its spatial resolution is usually low while our retrieved soil base respiration in this study has a high spatial resolution (8 km). Thus, the retrieved soil base respiration, in combination with the observed SOC from soil sample, could ensure consistency between the modeled and the observed SOC (Fig. 4) and at the same time significantly improve the spatial resolution of the estimated spatial pattern of the SOC.

The estimated spatial distribution of the SOC (Fig. 5) indicates that the value of the SOC, in general, is higher in the eastern regions and lower in the western regions. The highest SOC content is located in the northeast and southwest China, while the lowest value appears in the northwest desert or semi-desert regions. The region of south China, which has good heat and water conditions and an accordingly high NPP, has an SOC content that is not so high due to the high soil respiration. This spatial pattern of the SOC is consistent with that of soil base respiration.

The magnitude of the SOC depends on soil carbon input and output, i.e., the SOC content is determined by the NPP and soil heterotrophic respiration that are related with temperature and soil moisture. The higher SOC in east China is related with its high plant cover and NPP (Li et al., 2003). The highest SOC in northeast China is related to the high NPP and relative low soil respiration caused by relative low temperature. The area west of Yunnan province also has a high NPP and a relative low temperature and abundant water (Compilatory Committee of Climatic Atlas of P. R. China, 2002), which are helpful to soil organic carbon accumulation (Zhou et al., 2003). Although forests in southern China have higher NPPs than those in the northeast, the high temperature in south China also causes high soil respiration and, therefore, results in south China having less SOC than the northeast region (Zhou et al., 2004). North China has a relatively lower NPP and higher soil respiration and a low SOC content (Li et al., 2003). Northwest China has the lowest NPP and, accordingly, the lowest SOC content.

As the direct method of SOC estimation is based on observation of soil profiles and maps of soil type, it is suitable for comparing SOC content for different soil

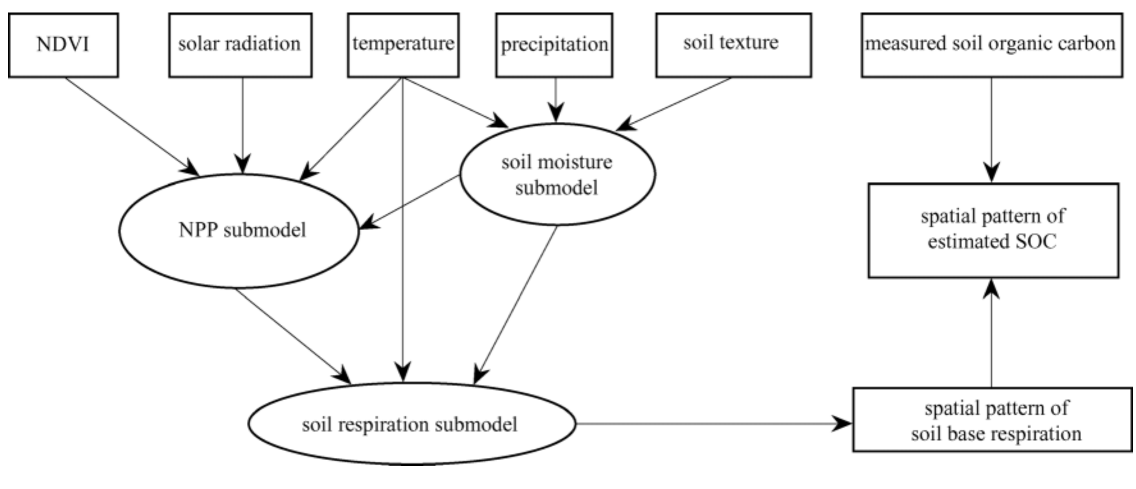

Fig. 2 Schematic flow of SOC estimation based on remote sensing data, process model, and measured SOC

Table 1 The base respiration of typical soils in China

soil type	soil base respiration (a_{ij})	temperature /°C	precipitation /mm
latosols	326.65	21.9	1495.1
latosolic red soils	317.51	20.1	1478.1
red soils	276.99	16.5	1380.1
yellow soils	270.52	16.2	1316.0
yellow brown soils	297.33	14.8	1036.0
brown soils	249.43	9.5	694.0
dark-brown soils	436.99	3.0	630.3
cinnamon soils	229.37	8.9	536.9
dark loessial soils	127.08	7.9	461.9
black soils	441.40	1.7	569.4
chernozems	253.40	3.3	363.4
castanozems	148.90	3.6	289.7
brown caliche soils	75.24	5.3	162.2
gray desert soils	71.27	6.4	141.8
gray-brown desert soils	68.51	6.7	87.3
sierozems	92.20	7.2	263.4
brown desert soils	58.52	8.1	57.4

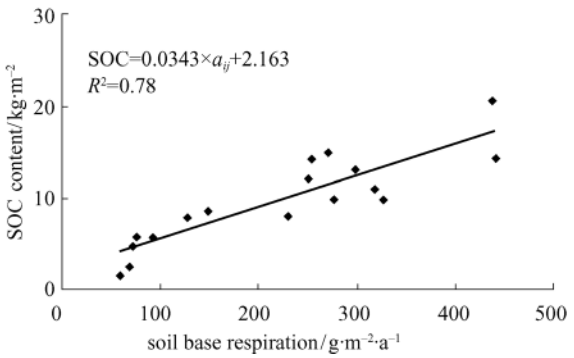

Fig. 3 Relationship between soil organic carbon content and soil base respiration

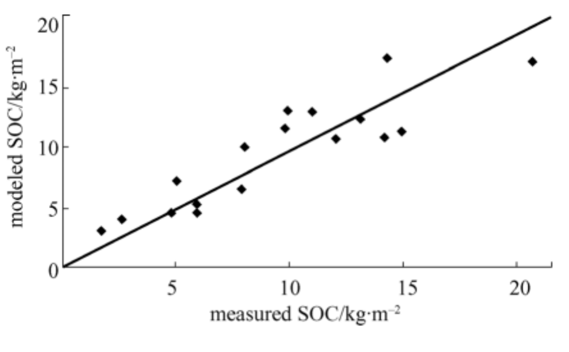

Fig. 4 Comparison between modeled and measured soil organic carbon content

types, but cannot estimate the SOC's spatial difference in the same soil type. Thus, its resolution is relatively low. For instance, the averaged spatial resolution of the estimated SOC by direct method is 21.04 × 10^6 square kilometer for soil types and 4.65 × 10^6 square kilometer for soil sub-types. Those are much larger than our estimated resolution of 64 square kilometer. Fig. 6 shows the spatial change of estimated SOC at a randomly selected south-to-north transect. Fig. 6a is sketch map of the selected transect, and Fig. 6b and Fig. 6c are spatial change of SOC estimated by our method and by the traditional direct method (Wang et al., 2001b), respectively. It illustrates that both methods has the similar spatial change trend but with different spatial resolutions.

As the global monthly NDVI data set of 8 km resolution has been widely used in vegetation dynamics monitoring and in the ecosystem process-based model, the retrieved spatial distribution of SOC of 8 km is helpful to match maps of SOC and vegetation and, therefore, it is better to use the coupled atmosphere-vegetation-soil carbon cycle models.

5 Discussion and conclusions

The Carbon cycle involving the atmosphere, vegetation and the soil is a hot research issue under the current global warming circumstance. Remote sensing data has a high spatial and temporal resolution and can be used for monitoring vegetation dynamics or estimating ecosystem carbon sequestration. There are two commonly used methods (i.e. direct and indirect methods) for estimating the spatial pattern of SOC. Each of them has both advantages and disadvantages. The spatial resolution of the direct method is relatively low, such that it can hardly distinguish the difference of SOC in the same soil type. The indirect method, on the other hand, has a relative high spatial resolution, but the simplification of some key parameters could potentially decrease the precision of the modeled SOC. In this study, we combined the advantages of both direct and indirect methods, which make our estimated SOC and its spatial pattern match with the observations and, at the same time, has relative high spatial resolution. As this method reflects the internal mechanism of the terrestrial carbon cycle, it is better than the results obtained by a purely spatial interpolation.

Although soil respiration is related to the SOC content, the relationship between actual soil respiration and the SOC content is not so well defined because of the influence of environmental factors, especially temperature and moisture. The relationship between soil base respiration and the SOC, however, is very strong, as the influences of climatic factors have been removed when retrieving soil base respiration. The statistical model between soil base respiration and the SOC content shows that the determinant coefficient (R^2) is 0.78. Consequently, we used a process-based model and the combined Van't Hoff soil respiration model to retrieve the spatial pattern of soil base respiration first, and then estimated the spatial pattern of SOC under the relationship between soil base respiration and the measured SOC. This method could significantly improve the spatial resolution and at the same time stay consistent with observations.

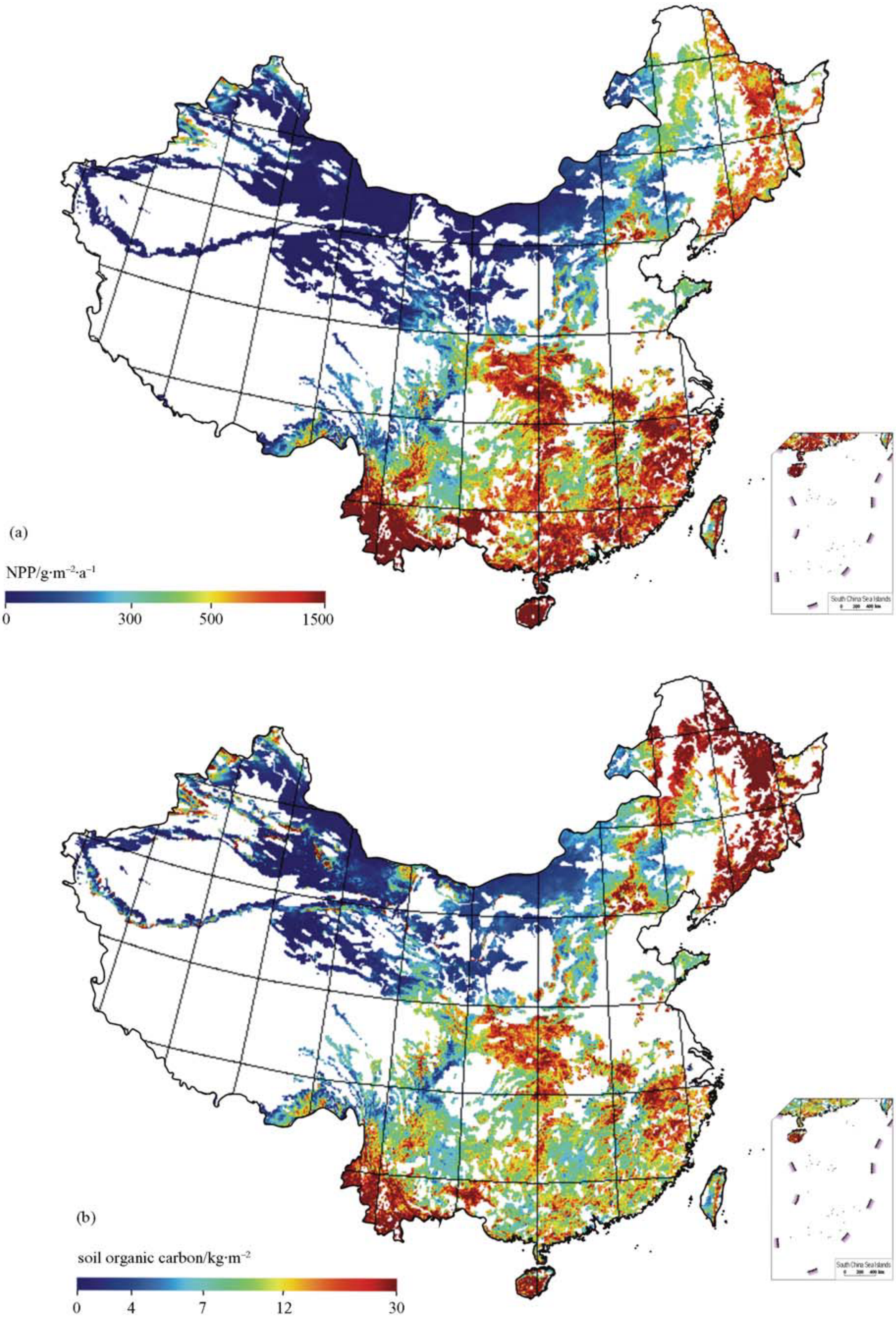

Fig. 5 Distribution maps of NPP and SOC content with 8 km spatial resolution (upper: NPP; lower: SOC)

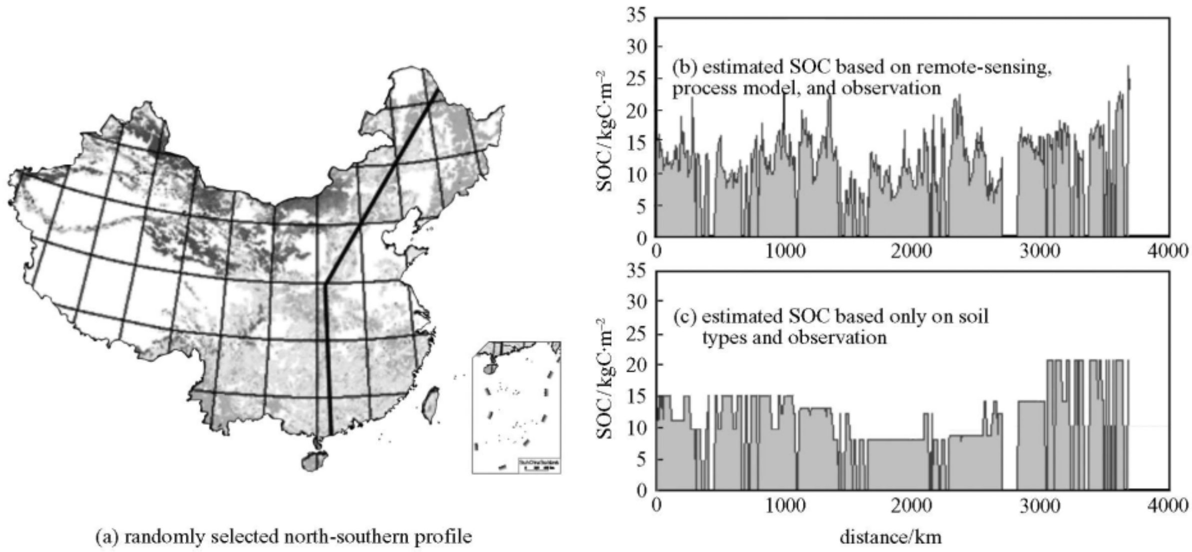

Fig. 6 Comparison of SOC content estimated by two different methods at a south-to-north transect

There are two factors that impact the precision of our estimated SOC content. One is inconsistency in the spatial scales of the corresponding spatial data. The spatial scale of the measured SOC is very small, which is much smaller than that of remote sensing data. Although the uncertainty of a model caused by different scales is one of the hottest research issues, it has not been well resolved as of now (Turner et al., 2005). The other factor impacting the precision of the estimated SOC is that not only does zonal climate factors impact soil base respiration but also some non-zonal factors (i.e. soil parent material) also impact soil base respiration (Trumbore, 2006). In this study, we used two strategies to reduce the potential impact of these non-zonal factors. One strategy is that we focused our research region in zonality soils that are mainly impacted by zonal climatic factors. The other one is that we did not estimate SOC by simply using meteorological data because the correlation between SOC and meteorological factors is only 0.3 (Zhou et al., 2003). Instead, we integrated meteorological data with remote sensing data and a process-based carbon cycle model to retrieve a better index (i.e. soil base respiration). All of these significantly improved the precision of SOC estimation.

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References

Compilatory Committee of Climatic Atlas of P. R. China (2002). Climatic Atlas of China. Beijing: Meteorological Press (in Chinese)

Fang J Y, Liu S H, Zhao K (1998). Factors affecting soil respiration in reference with temperature's role in the global scale. Chin Geogr Sci, 8(3): 246–255

Fang J, Piao S, Field C B, Pan Y D, Guo Q H, Zhou L M, Peng C H, Tao S (2003). Increasing net primary production in China from 1982 to 1999. Front Ecol Environ, 1(6): 293–297

Field C B, Randerson J T, Malmstrom C M (1995). Global net primary production: Combining ecology and remote sensing. Remote Sens Environ, 51: 74–88

Foley J A (1995). An equilibrium model of the terrestrial carbon budget. Tellus, 47B: 310–319

Högberg P, Nordgren A, Buchmann N, Taylor A F, Ekblad A, Högberg M N, Nyberg G, Ottosson-Löfvenius M, Read D J (2001). Large-scale forest girdling shows that current photosynthesis drives soil respiration. Nature, 411(6839): 789–792

Jin F, Yang H, Cai Z C, Zhao Q G (2001). Calculation of density and reserve of organic carbon in soils. Acta Pedol Sin, 38(4): 522–528 (in Chinese).

Kern J S (1994). Spatial patterns of soil organic carbon in the contiguous United States. Soil Sci Soc Am J, 58: 439–455

King A W, Post W M, Wullschleger S D (1997). The potential response of terrestrial carbon storage to changes in climate and atmospheric CO_2. Climat Change, 35: 199–227

Lal R (2002). Soil organic dynamics in cropland and rangeland. Environ Pollut, 116: 353–362

Li K R, Wang S Q, Cao M K (2003). Carbon storage in vegetation and soil of China. Sci China (Ser D), 33(1): 72–80 (in Chinese)

Li Z, Zhao Q G (2001). Organic carbon content and distribution in soils under different land uses in tropical and subtropical China. Plant Soil, 231: 175–185

Luo Y, Wan S, Hui D, Wallace L L (2001). Acclimatization of soil respiration to warming in a tall grass prairie. Nature, 413 (6856): 622–625

Merry C J, Levine E R (1995). Methods to assess soil carbon using remote sensing techniques. In: Lal R, Kimble J, Levine E, Stewart B A eds. Soils and Global Change. Boca Raton, FL: CRC Press, 265–274

National Soil Survey Office (1995). Chinese Soil Census Records (Volumes 1–6). Beijing: China Agriculture Press (in Chinese)

National Soil Survey Office (1998). Soils of China. Beijing: China Agricultural Press, 1–1252 (in Chinese)

Palmer C J, Smith W D, Conkling B L (2002). Development of a protocol for monitoring status and trends in forest soil carbon at a national level. Environ Pollut, 116: 209–219

Parton W J, Mckeown B, Kircher V (1992). Century User Manual. Colorado, USA: Colorado State University NREL Publication

Parton W J, D S Ojima, D S Schimel (1995). Models to evaluate soil organic matter storage and dynamics. In: Carter M R, Stewart B A eds. Structure and Organic Matter Storage in Agricultural Soils.New York: CRC Press, 421–448

Piao S L, Fang J Y, Guo Q H (2001). Application of CASA model to the estimation of Chinese terrestrial net primary productivity. Acta Phytoecol Sin, 25(5): 603–608 (in Chinese)

Post W M, Izaurralde R C, Mann L K, Bliss N (2001). Monitoring and verifying changes of organic carbon in soil. Climat Change, 51: 73–99

Post W M, Peng T H, Emanuel W R, King A W, Dale V H, De Angelis D L (1990). The global carbon cycle. Am Sci, 78:310–326

Potter C S, Klooster S A (1997). Global model estimates of carbon and nitrogen storage in litter and soil pools: response to changes in vegetation quality and biomass allocation. Tellus, 49B, 1–17

Potter C S, Randerson J T, Field C B, Matson P A, Vitousek P M, Mooney H A, Klooster S A (1993). Terrestrial ecosystem production: A process model based on global satellite and surface data. Global Biogeochem Cy, 7(4): 811–841

Prentice I C (2001). The carbon cycle and atmospheric carbon dioxide. In: Climate Change 2001: The Scientific Basis (IPCC). Cambridge: Cambridge University Press, 184–237

Prince S D, Goward S N (1995). Global primary production: a remote sensing approach. J Biogeogr, 22: 815–835

Raich J W, Potter C, Bhagawati D (2002). Interannual variability in global soil respirationg, 1980–94. Global Change Biol, 8: 800–812

Reichstein M, Rey A, Freibauer A, Tenhunen J, Valentini R, Banza J, Casals P, Cheng Y F, Grünzweig J M., Irvine J, Joffre R, Law B E, Loustau D, Miglietta F, Oechel W, Ourcival J M, Pereira J S, Peressotti A, Ponti F, Qi Y, Rambal S, Rayment M, Romanya J, Rossi F, Tedeschi V, Tirone G, Xu M, Yakir D (2003). Modeling temporal and large-scale spatial variability of soil respiration from soil water availability, temperature and vegetation productivity indices. Global Biogeochem Cy, 17(4): 1104

Ruimy A, Saugier B (1994). Methodology for the estimation of terrestrial net primary production from remotely sensed data. J Geophys Res, 99, 5263–5283

Sun R, Zhu Q J (2000). Distribution and seasonal change of Net Primary Productivity in China from April, 1992 to March, 1993. Acta Geogr Sin, 55(1): 36–45 (in Chinese)

Trumbore S (2006). Carbon respired by terrestrial ecosystems - recent progress and challenges. Global Change Biol, 12, 141–153

Turner D P, Ritts W D, Cohen W B, Maeirsperger T K, Gower S T, Kirschbaum A A, Running S W, Zhao M S, Wofsy S C, Dunn A L, Law B E, Campbell J L, Oechel W C, Kwon H J, Meyers T P, Small E E, Kurc S A, Gamon J A. (2005). Site-level evaluation of satellite-based global terrestrial gross primary production and net primary production monitoring. Global Change Biol, 11(4): 666–684

Wang S Q, Tian H Q, Liu J Y, Pan S F (2003). Pattern and change of soil organic carbon storage in China: 1960s–1980s. Tellus, 55B: 416–427

Wang S Q, Zhou C H, Li K R, Zhu S L, Huang F H (2001a). Study on spatial distribution character analysis of soil organic carbon reservoir in China. J Geogr Sci, 11(1): 3–13

Wang S Q, Zhou C H, Liu J Y, Li K R, Yang X M (2001b). Simulation analyses of terrestrial carbon cycle balance model in northeast China. Acta Geogr Sin, 56(4): 390–400 (in Chinese)

Wu H B, Guo Z T, Peng C H (2003). Land use induced changes of organic carbon storage in soils of China. Global Change Biol, 9: 305–315

Yu M, Gao Q, Xu H M, Liu Y H (2001). Response of vegetation distribution and primary production of the terrestrial ecosystems of China to climatic change. Quater Sci, 21(4): 281–293 (in Chinese)

Zhao Q G, Gong Z T (1991). Soil Resources in China. Nanjing: Nanjing University Press, 72–100 (in Chinese)

Zhou T, Shi P J, Sun R, Wang S Q (2004). The impacts of climate change on net ecosystem production in China. Acta Geogr Sin, 59(3): 357–365 (in Chinese)

Zhou T, Shi P J, Wang S Q (2003). Impacts of climate change and human activities on soil carbon storage in China. Acta Geogr Sin, 58(5): 727–734 (in Chinese)

Zhou T, Yi C X, Shi P J, Luo J Y (2002). A feedback mechanism research on the carbon cycle and temperature of terrestrial surface system. Geogr Res, 21(1): 45–53 (in Chinese)