


Taking climate, land use, and social economy into estimation of carbon budget in the Guanzhong-Tianshui Economic Region of China

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Abstract Carbon sequestration is an indispensable ecosystem service provided by soil and vegetation, so mapping and valuing the carbon budget by considering both ecological and social factors is an important trend in evaluating ecosystem services. In this work, we established multiple scenarios to evaluate the impacts of land use change, population growth, carbon emission per capita, and carbon markets on carbon budget. We quantified carbon sinks (aboveground and belowground) under different scenarios, using the Carnegie-Ames-Stanford Approach (CASA) model and an improved carbon cycle process model, and studied carbon sources caused by human activities by analyzing the spatial distribution of human population and carbon emission per capita. We also assessed the net present value (NPV) for carbon budgets under different carbon price and discount rate scenarios using NPV model. Our results indicate that the carbon budget of Guanzhong-Tianshui Economic Region is surplus: Carbon

sinks range from 1.50×10^{10} to 1.54×10^{10} t, while carbon sources caused by human activities range from 2.76×10^5 to 7.60×10^5 t. And the NPV for carbon deficits range from 3.20×10^{11} RMB to 1.52×10^{12} RMB. From the perspective of ecological management, deforestation, urban sprawl, population growth, and excessive carbon consumption are considered as the main challenges in balancing carbon sources and sinks. Levying carbon tax would be a considerable option when decision maker develops carbon emission reduction policies. Our results provide a scientific and credible reference for harmonious and sustainable development in the Guanzhong-Tianshui Economic Region of China.

Keywords Carbon budget · Scenario · The Guanzhong-Tianshui Economic Region

Introduction

The entry into force of Paris Agreement on climate change means that 192 states and the European Union agreed that the government can guide people to reduce carbon emissions through suitable guidance or mandatory measures to ease the pressure on climate change. The Chinese government pledges to reach a peak of emissions no later than 2030 and to slash CO₂ emissions per unit of the gross domestic product (GDP) by 60–65% from the 2005 level. Under this background, the balance of the carbon exchanges (incomes and losses) among the carbon reservoirs or in one specific loop of the carbon cycle (e.g., the cycle of biosphere and atmosphere) is called carbon budget, which takes the emissions of CO₂ from deforestation and fossil fuel combustion, the absorption of CO₂ into oceans, and the buildup of CO₂ into the atmosphere into account (Kauppi et al. 1992). And the spatial and temporal changes of the carbon budget have an important influence

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on the ocean warming, the decrease of the Arctic sea ice area, and the rise of the sea level (IPCC 2014). So, the quantification of carbon budget for regions and globe can improve our understanding of the relationships among carbon reservoirs in the context of global change and facilitate carbon emission reduction policy-making. However, these definitions of carbon budget are described from the term in biophysics, not in ecological geography. Ecological geography researchers focus more about how carbon cycle system effect in earth ecosystem as a whole role. Furthermore, the impact of human activities on the ecological environment is increasingly strengthened, so it is necessary to take climate, land use, and social economy synthetically into the estimation of carbon budget.

With the development of carbon cycle model in terrestrial ecosystem, the understanding of carbon balance is promoting. After the development of classic ecosystem productivity models such as Miami, Thornthwaite, and Chikugo (Lieth 1972; Seino and Uchijima 1985), the parameter models of primary production (Lieth 1975) have been widely adopted as it can describe the ecological process. The biochemical model of photosynthetic CO₂ assimilation (Farquhar et al. 1980) and the model of stomatal conductance predicting rely on photosynthesis (Ball et al. 1987) made it possible to develop the process-based terrestrial models, such as the Farquhar biochemical growth model (Farquhar et al. 1980). Based on multiple-scale geography spatial database and the vegetation-climate relationships, the process-based terrestrial models were used to simulate the potential vegetation distribution and to predict the impact of climate change on terrestrial carbon balance (Gao et al. 2003; Rosenzweig et al. 2014; Vukicevic et al. 2001; Wang et al. 2013). Dynamic process-based models have contributed much to the exploration of biogeochemical cycle, especially the terrestrial carbon cycle dynamic change due to vegetation composition change and LUCC (land use and cover change) (Girardin et al. 2008; Pan et al. 2014; Shen et al. 2013; Zhang et al. 2009).

Remote sensing technology has been considered as an effective tool to provide direct estimation of vegetation characteristics. The remote sensing parameter models (e.g., GLOPEM, VPM, EC-LUE), which based on empirical models and the remote sensing observation data, are more and more widely used in the estimation of terrestrial biomass (Prince and Goward 1995; Song et al. 2013; Xiao et al. 2004; Yan et al. 2007). Compared with the process-based terrestrial models, the input data and parameter of remote sensing parameter models can be obtained more easily. But research studies in this field generally rely on empirical parameters rather than observation data, which would influence the precision of the models. Therefore, the combination of process-based terrestrial model and remote sensing can be considered as a more effective method to simulate terrestrial ecosystem carbon cycle (e.g., the boreal ecosystem productivity simulator model, GLOPEM-CEVSA, and CI-LUE) (Wang et al.

2015; Yan et al. 2007; Zhang 2009). For example, Wang et al. modeled carbon fluxes of different forests by coupling a remote sensing model with an ecosystem process model (Wang et al. 2011). Chen simulated the NEP of terrestrial ecosystems using BEPS and explored the feasibility of optimizing ecosystem photosynthetic and respiratory parameters from the seasonal variation of the net carbon flux (Chen et al. 2015). The coupling of remote sensing, field campaign, and mechanistic and empirical modeling is an effective method to monitor spatiotemporal carbon dynamics (Berberoglu et al. 2015). Footprint is a frequently used method to study the impact of human beings on ecosystems (Fang 2015). Agricultural expansion impacts were evaluated by assessing ecological and environmental footprints between 1960 and 2005 (Viglizzo et al. 2011). Changes in carbon stock were quantified in Colombia by assessing oil palm cultivation expansion combined with offsetting factors that reduce carbon emissions (Henson et al. 2012). Facing such a complex system, it is necessary to predict the responses of ecosystems to change environmental conditions and management practices and to compare the estimated provided services in terms of different scenarios (Laflower et al. 2016; Schaubroeck et al. 2016). In the recent few years, the response of carbon budget to LUCC has attracted more and more researchers' attention to the changes of energy balance, productivity, and supplies and beneficiaries of ecosystem services. For example, the impacts of three cities' urbanization on ecosystem goods and services are evaluated (Eigenbrod et al. 2011; Schneider et al. 2012); the impacts of land use changes on ecosystem service value in the Loess Plateau was estimated through land use monitoring (Li and Ren 2011). However, until recently, there is some lack of knowledge about taking consideration of climate, land use change, and social economy to simulate the terrestrial carbon budget (Cabello et al. 2012; Masek et al. 2015; Muraoka and Koizumi 2009).

In this study, carbon budget is defined as the difference of carbon sink and carbon source. The processes of carbon sink and source are completely opposite: Carbon sink removes carbon dioxide (CO₂) from the atmosphere, while carbon source puts CO₂ into the atmosphere. Considering factors of climate, land use, and social economy, this article establishes multiple scenarios to measure and evaluate the net present value (NPV) of carbon budgets synthetically and spatially. Based on the Carnegie-Ames-Stanford Approach (CASA) model, remote sensing, and carbon cycle process model, we estimated carbon sequestration (aboveground and belowground) under different scenarios of climate and land use in the Guanzhong-Tianshui Economic Region, China. At the same time, we studied carbon sources caused by human activities by analyzing the density and spatial distribution of human population. We also assessed the economic value of carbon budgets under different carbon price and discount rate scenarios, using NPV. Based on these results, we analyzed the

impacts of land use, climate change, population growth, carbon emissions, and carbon markets to carbon budgets in three different scenarios. Our results may provide quantitative references to support regional carbon accounting and support policy decision-making that consider climate, land use, and social economy.

Study area and data

Study area

The Guanzhong-Tianshui Economic Region (GTER) is located in the center of the Asia-Europe continental bridge (longitude 104° 34' 47" E–110° 48' 38" E, latitude 33° 21' 37" N–35° 51' 15" N), including seven administrative regions across the provinces Shaanxi and Tianshui of Gansu. This area is moderately dry with a warm climate: The mean annual precipitation is 550 mm year⁻¹, and the annual mean air temperature is between 11 and 13 °C. The main soil types of this region are brown soil, cinnamon soil, and Lou soil. The Qinling Mountains is a major east-west mountain range with a rich biodiversity and natural habitats for rare animals in south of the study area. And the Loess Plateau is located in the north of this area. Between these two mountain ranges, the fertile land of the Guanzhong Plain supplies major grain production for GTER (Fig. 1). Ecosystems such as the Qin Mountains and Guanzhong Plain are important for water yield, water interception, soil conservation, agricultural production, and carbon sequestration for GTER (Qin et al. 2015). As a hybrid system with multiple land use types, GTER is a

complex ecosystem with complicated and diverse carbon budgets.

This region's cultural landscape, formed over thousands of years, is a valuable asset and provides a wealth of information about human activities. At the end of 2014, the area had a population of about 43 million, making it one of the most crowded regions in western China. As an essential region for western development, its social and economic development has a far-reaching influence on China. The Guanzhong Plain supplies fertile soil for agriculture and topographic conditions conducive for city formation and development. Recent few decades, urban expanded with a high speed, urban land use area increase of 42.39% from the year of 2000 to 2014. In 2014, the area of cropland is 3,509,810 ha, forestland area is 1,868,680 ha, grassland area is 2,273,800 ha, water area is 81,645.3 ha, urban area is 200,867 ha, and unused land area is 57,296 ha. The balance between ecological protection and the high speed economic development face challenges. Therefore, this study focuses on the relationship between carbon sequestration and carbon sources caused by human activities in this region.

Data sources

The data sources of this study are as follows: (1) basic geographic information data of GTER (roads, rivers, administrative boundaries, and digital elevation model (DEM)), provided by the National Basic Information Center; (2) meteorological data such as solar radiation, precipitation, temperature, and evapotranspiration, obtained from the China Meteorological Data Sharing Servicing System; (3) remote sensing images (MODIS) with a

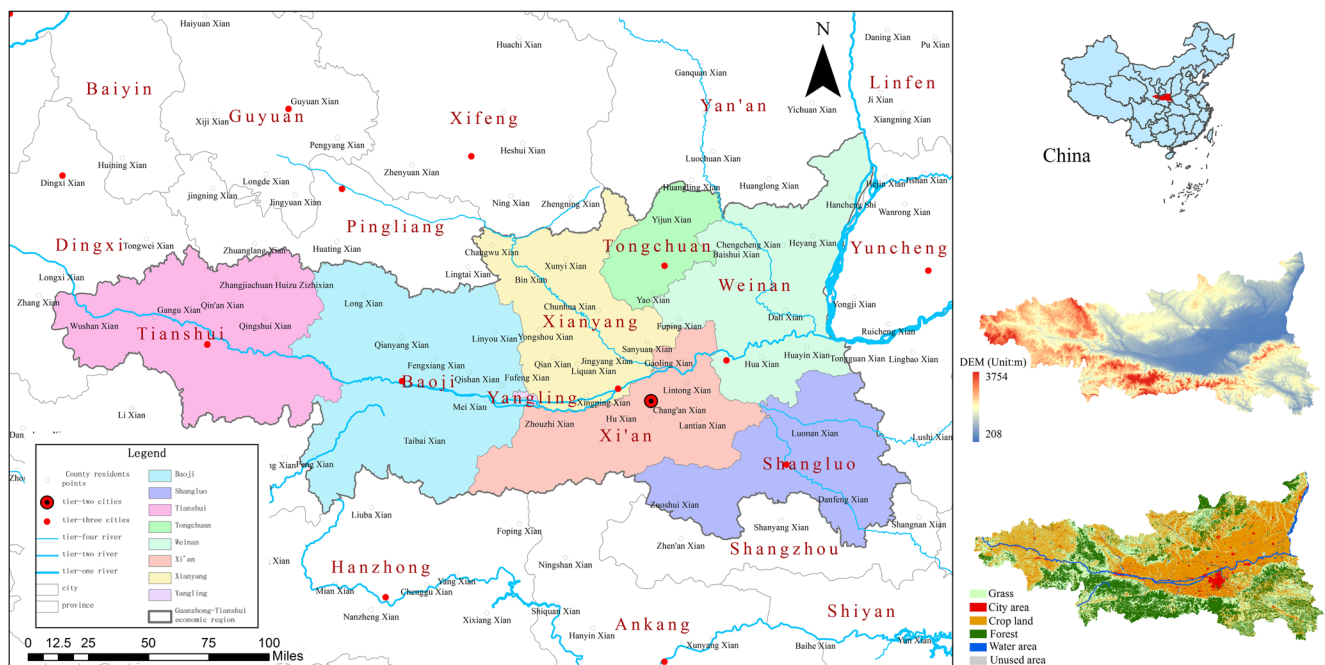


Fig. 1 Location of the study area

resolution of 250×250 m, downloaded from the Geographical Data Cloud; (4) land use in the year 2000, 2005, 2010, and 2014, obtained by remote sensing image interpretation (accuracy 80%); (5) populations. Population of 2014 derived from books of the Statistical Yearbooks of the provinces of Shaanxi and Gansu (Gansu Provincial Bureau of Statistics 2015; Shaanxi Provincial Bureau of Statistics 2015). Population growth rate in scenario A derived from the 2015 Revision of World Population Prospects (United Nations, Department of Economic and Social Affairs, Population Division 2015). Population growth rates in scenarios B and C derived from the population in the 12th and 14th report of the 2050 China Energy and CO₂ Emission Report, respectively (2050 China Energy and CO₂ Emission Research Group 2009). (6) Carbon emission per capita. The carbon emission per capita of 2014 derived from China Energy Statistical Yearbooks of 2015, and that of scenarios A, B and C derived from the enhanced low-carbon scenario, low-carbon scenario, and baseline scenario of the 14th report in the 2050 China Energy and CO₂ Emission Report, respectively (2050 China Energy and CO₂ Emission Research Group 2009). (7) Carbon price derived from the prices of Chinese carbon trading pilots in 2014. (8) Discount rates in 2050 was set according to the lending rate of 5 years or more of 2011 to 2014 (between 5.9 and 7.05%) (The People’s Bank of China 2015).

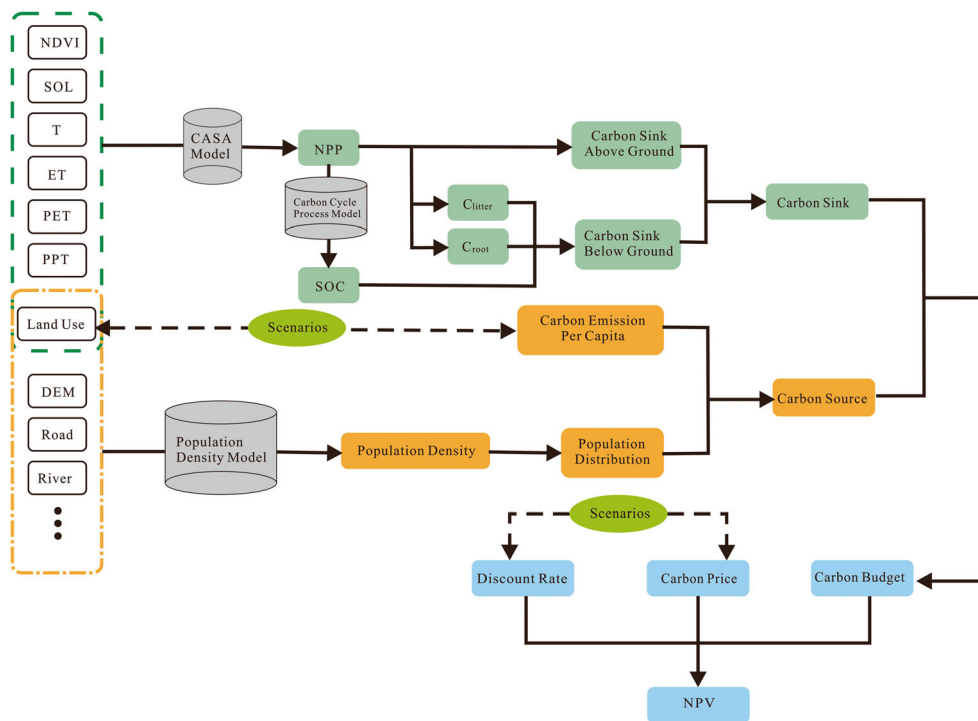
Models

In this study, we estimated carbon budgets and their net present values based on basic database (Fig. 2).

Most carbon sequestration studies originally rely on biomass estimates, where prediction equations are presented for green and dry weights of aboveground tree components (Field et al. 1995; Maia et al. 2010; Prince and Goward 1995; Temesgen et al. 2015). Additionally, many equations have been developed to estimate biomass components of trees and shrubs in various ecosystems. Tree biomass estimates generally rely on additional properties (i.e., the total tree biomass should equal the sum of the components); using parameter restrictions and considering residual contemporaneous correlations allow more efficient estimates and consistent prediction intervals (Carvalho and Parresol 2003). Carbon sequestration is an ecosystem service that is usually classified as a regulating service. Estimating terrestrial ecosystems, carbon sequestration generally includes three components: aboveground biomass, soil carbon, and the carbon sequestered in litter and roots (Novara et al. 2015).

In contrast, social statistics are used to estimate human-driven carbon emissions. The calculation methods of carbon source mainly include measurement, material balance algorithm, and discharge coefficient, among which the last method is the most widely used. The coefficients of carbon dioxide emission have a variety of standards, such as Intergovernmental Panel on Climate Change (IPCC), DOE/EIA, and ORNL. And most researchers take the factors of population and ecological development as main factors in the estimation of carbon emission (Guo 2011). To better express carbon consumption from a spatial perspective, this study takes

Fig. 2 Framework of study



population density as a variable to describe carbon sources caused by social and economic activities. Policy instruments, such as conservation subsidies, protected lands, land conversion taxes, and excise taxes, are considered effective tools in protecting the ecological environment (Mann et al. 2012).

Future scenarios

The carbon cycle system involves complex processes of material circulation and energy flow (Zhang et al. 2016) and hence the estimation of carbon budget. IPCC AR5 (the Fifth Assessment Report) provided multiple global scenarios in 2100 following the representative concentration pathways (RCPs). However, the spatial resolution of this data is too large (1×1 km) for this study area. In this study, we choose land use change, population growth, and emission reduction policy to simulate the future scenarios for carbon budget.

Land use change, as an important cause of human greenhouse gas emissions, has a strong legacy effect on carbon fluxes (Aragao et al. 2014; Köchy et al. 2015; Wasak and Drewnik 2015). Traditionally, land use change includes slash and burn deforestation, cultivation and abandonment, and so on (Aragao et al. 2014). In GTER, the challenge is not slash and burn deforestation, for most forest areas has been well protected, but the high speed urban expansion. In this study, land use in 2050 was predicted using IDRISI, a software based on CA-Markov-based model. Land use of 2014 was chosen as a baseline. In scenario A, urban growth is excluded, agricultural land growth is limited, and forest is well protected and developed. In scenario B, the future landscape change follows the policies that implemented during 2000 to 2010. In scenario C, a loosening of current policies to allow free market forces across all parts of the landscape, but still within the range of what stakeholders think is feasible.

Population growth results in rising not only carbon dioxide that human respiration evolves but also the combustion of fossil fuels. In the past few decades, Chinese government was committed to controlling population growth through the family planning policy. However, the huge population base is still a main reason for the huge total energy consumption. We applied the Chinese population growth rates of 2014 to 2050 multiplied by population of GTER as the future populations.

We choose the carbon emission on future scenarios to simulate the effects of emission reduction policy on carbon balance. To combine the emission cuts and population, we used carbon emission per capita in each scenario (Table 1).

As an effective emission reduction policy, carbon tax policies were adopted by many developed countries. China approved a series of pilot cities/provinces of

carbon emissions trading in 2013. This may be a signal that China is starting to levy a carbon tax in the future. Carbon prices used in this study are based on 2014 research results, at 29.6, 70.2, and 130.9 RMB, representing the lowest, average, and highest carbon prices in China. During 2011 to 2014, the lending rate of 5 years or more was between 5.9 and 7.05% (The People's Bank of China 2015). Based on this condition of China, we used 5, 6, and 7% as the discount rates for this study.

Carbon budget

The difference in NPV of carbon sequestrations minus carbon emissions indicates whether there are carbon deficits or profits. If the value is positive, then carbon sequestrations in the area can satisfy local needs, with a surplus remaining. This is defined as a carbon profit. Conversely, if the value is negative, then the carbon sequestrations provided by the area cannot satisfy local needs and carbon must be imported. This reflects a carbon deficit.

Carbon sink

In this article, carbon sink is classified into aboveground and belowground sequestration.

1. Aboveground carbon sequestration

Net primary production (NPP) refers to the rate at which all plants in an ecosystem produce useful chemical net energy. In this paper, NPP is calculated using the CASA model (Field et al. 1995; Potter et al. 1993), generalized using the following expressions:

$$NPP_a(x, t) = APAR(x, t) \times \varepsilon(x, t) \quad (1)$$

$$C_a(x, t) = NPP_a(x, t) \times \sigma \quad (2)$$

$APAR(x, t)$ represents the amount of photosynthetic active radiation ($\text{MJ m}^{-2} \text{ month}^{-1}$) absorbed by element x in month t , and $\varepsilon(x, t)$ is a factor that reflects the efficiency (gC MJ^{-1}) with which light energy is used to produce organic compounds in grid x for month t . $NPP_a(x, t)$ represents the amount of net primary production aboveground; $C_a(x, t)$ represents the carbon aboveground, and σ is the carbon content of organic matter, $\sigma = 0.4$.

2. Belowground carbon sequestration

Belowground carbon consists of three parts: the soil organic carbon (SOC), the carbon in litter, and the carbon in biological roots. For the aboveground carbon cycle, the estimation of NPP

Table 1 Scenarios of carbon budget

Year	Urban growth	Carbon emission per capita (t C)	Population growth rate	Carbon price (RMB per ton)	Discount rate
2014	Baseline	2.17	–	–	–
2050A	Protection	0.95	–0.79%	130.9	7%
2050B	Constrained development	1.64	5.28%	70.2	6%
2050C	Open development	2.24	6.74%	29.6	5%

was based on photosynthesis process. The differences among cropland, woodland, and grassland are described by the remote sensing images directly. As to the belowground biomass, we consider the litter and roots of vegetation. Considering that the biomass of litter and root varies from one biome to another, we used the ratios of biomass belowground and aboveground (Table 2) to estimate the carbon sequestration for the belowground biomass of different biome (cropping land, forest, and grassland) refer from literature (Canga et al. 2013; Ma 2012; Ren 2012).

$$C_u = SOC + C_{litter} + C_{root} \tag{3}$$

The parameters C_u , SOC, C_{litter} , and C_{root} describe the amount of carbon belowground, SOC, litter carbon, and root carbon, respectively. The theoretic relationship of the litter part of net primary productivity (NPP) and SOC stocks is well established (Abbasi et al. 2015; Gumus and Seker 2015; Todd-Brown et al. 2013), but the long-term effect of climate change on carbon submission is still unclear (Köchy et al. 2015).

Because of limited data sources, SOC is calculated indirectly. Soil basic respiration (SBR) is an indispensable variable to measure the rate of carbon dioxide (CO₂) release from the soil (Field et al. 1995). Previous studies have confirmed a significantly negative correlation between SBR and SOC (You 2012); as such, SOC can be quantified based on an SBR and a regression model.

Calculations of belowground carbon assume that the atmosphere-vegetation-soil system is in a balanced state. Based on the physical process of soil respiration, organic carbon sequestered through NPP equates to the organic carbon decomposed by soil respiration. This relationship is expressed as $NPP = R_h + R_L = R_H$, where R_h represents soil humus decomposition, R_L represents deciduous carbon mineralization, and R_H represents

Table 2 Specific relations between carbon in root/litter and aboveground of different land use

Specific relation	Cropping land	Forest	Grassland
Root/aboveground	18.85%	28.3%	169%
Litter/aboveground	45.6%	14.39%	25.3%

total soil respiration. An improved carbon cycle process model (Zhou et al. 2007) is chosen to invert SBR based on remote sensing imagery, because this approach takes moisture factors (annual precipitation and potential evapotranspiration) into consideration, thereby aligning the model to real-world arid and semiarid conditions.

Based on this discussion, soil basic respiration is calculated using the following expressions:

$$A_{ij} = \frac{R_H}{\exp(b \times T) \times y} \tag{4}$$

$$y = \frac{1}{1 + 30.0 \times \exp(-8.5 \times x)} \tag{5}$$

$$x = \frac{PPT}{PET} \tag{6}$$

$$R_H = NPP \tag{7}$$

The parameters A_{ij} , PPT, and PET describe soil basic respiration, annual precipitation, and potential evaporation, respectively. The constant factor b reflects temperature sensitivity.

We used regression analysis to evaluate 60 samples of soil basic respiration inversion results (from the year 2000) and the second soil census data. These results are combined with soil basic respiration data for the year 2014 to estimate SOC (Figs. 3 and 4).

$$SOC = f(A_{ij}) \tag{8}$$

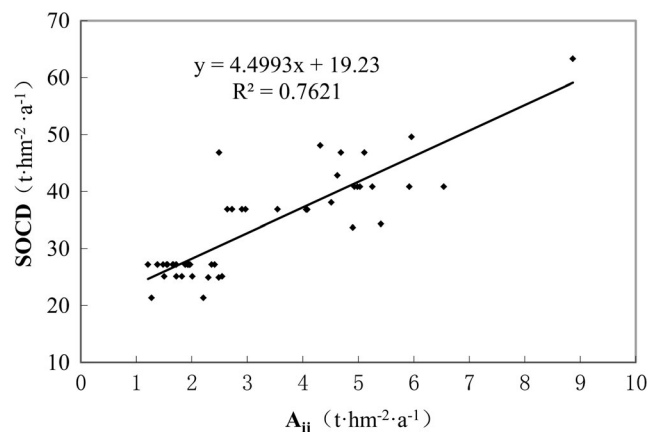


Fig. 3 Relationship of SOC content and soil basal respiration

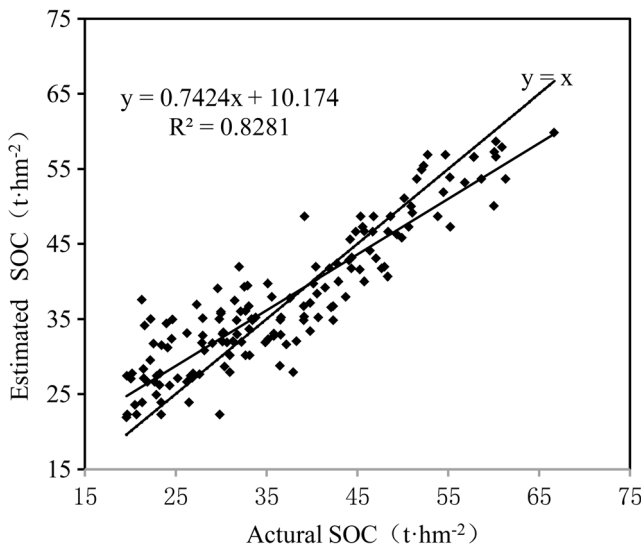


Fig. 4 Relationship between measured SOC and estimation value with model

where SOC is the amount of soil organic carbon and a linear function with A_{ij} as the independent variable.

3. Carbon source

In this study, the source of ecosystem services is considered the area where carbon is sequestered in vegetation and soil. In carbon sources, vegetation and soil fix carbon as the following expression:

$$C_s = \sum_{x=1}^X C_a(x, t) + \sum_{y=1}^Y C_u(y, t) \tag{9}$$

where C_s is the carbon sequestration aboveground and belowground and $C_a(x, t)$ and $C_u(y, t)$ correspond to aboveground and belowground carbon, respectively, for grid x and y in year t .

Carbon source

In this study, we used carbon release figures based on land use change, population, and carbon emission per capita. Potential stored carbon releases due to fire and other vegetation and soil disturbances are outside the scope of this study. Population density and per capita carbon emissions are combined with spatially express carbon released through social and economic activities.

$$C_e = \sum_{x=1}^X \rho(x) \times \varphi(x) \tag{10}$$

where C_e is carbon emissions caused by human activities, $\rho(x)$ represents the population density of grid x , and $\varphi(x)$ is carbon emission per capita of grid x . The X is the number of grid in study area. $\varphi(x)$ is set to be different constant in the four different scenarios (Table 1).

Population density is the population in a given unit area, showing the level of development. There are differences between urban and rural regions; as such, for calculation purposes, land type is divided into urban and rural units based on land use and administrative maps. For quantization purposes, population coefficient is defined as the weighted sum of factors after respectively maximum normalization.

$$POP_{ij} = P_{ir} \times \frac{V_{jr}}{\sum_{j=1}^h V_{jr}} + P_{iu} \times \frac{V_{ju}}{\sum_{j=1}^k V_{ju}} \tag{11}$$

where POP_{ij} is the population of the j th pixel in the i th administrative district, P_{ir} is the rural population of the i th administrative district, P_{iu} is the urban population of the i th administrative district, h is the rural pixel number of the i th administrative district, k is the urban grid number of the i th administrative district, V_{jr} is the rural population coefficient of the j th pixel in the i th administrative district, and V_{ju} is the urban population coefficient of the j th pixel in the i th administrative district.

The urban population coefficient is based on urban area and calculated using the expression below (Tian et al. 2004):

$$V_{ij} = A_j \times \ln A_i \times \exp \left[- \left(\frac{r_j}{\sqrt{A_i/\pi}} \right)^\sigma \right] \\ = A_j \times \ln A_i \times \exp [-1.9874r_j^{1.06}A_i^{-0.6}] \tag{12}$$

where V_{ij} is the population density coefficient of j grid in i urban district, A_j is the urban area of j grid, A_i is the area of i urban district, and r_j is the Euclidean distance of the center of j grid to the urban center. The parameter σ describes the different state of urban development and is set at $\sigma = 1.05$, which is calculated using economic statistical data (Zeng 2013).

Referring to argument evaluation of a previous study, land use, DEM, distance from road, and distance from the river are applied as factors that relate to rural population density. The rural population coefficient is the weighted sum of these factors after respectively maximum normalization. The weight of land use is calculated using an overlay analysis with land use and housing estate distribution maps. The weights of roads and rivers are calculated using buffer analysis and overlay analysis, respectively, based on road and river vector data and housing estate distribution maps.

Net present value

In economics, net cash flows in different periods are translated into equivalent cash values using a benchmark yield or discount rate, which is called NPV. NPV is widely used to estimate the earnings of different programs or investments, including air pollution control, soil fertility management, and greenhouse gas emission reduction. In this study, we combine

NPV with discount rate to analyze the NPV of carbon, leading to more precise results than other methods can yield.

We established six situations based on three carbon prices and two discount rates to estimate NPV values of carbon budgets. Python programming was used to factually represent the mode built by Polglase et al. (2013). The calculation formula follows

$$NPV_{ijs} = PVB_{ij} - PVC_{js} \tag{13}$$

where NPV_{ijs} represents the current benefits, PVB_{ij} the current carbon sequestration value, and PVC_{ij} the cost of each situation.

$$PVB_{ij} = \sum_{t=0}^T \frac{P_i \times q_{ij}}{(1+r)^t} \tag{14}$$

Further, P_i represents the carbon prices, q_{ij} the annual carbon sequestration, r the annual discount rate, and t the time periods.

$$PVC_{js} = EC_j + \sum_{t=0}^T \frac{MC \times PFE_s}{(1+r)^t} \tag{15}$$

Finally, PFE_s represents the opportunity cost of afforestation, EC_j the one-time expenses, and MC the cost of carbon maintenance and trading, and EC_j and MC are constant values in a certain research area.

Results

Carbon budgets in different scenarios

As a whole, the carbon sinks are larger than carbon source. The carbon budgets of GTER in all of four scenarios in this study are surplus, ranging from 1.50×10^{10} to 1.54×10^{10} t (Fig. 7). Among all the scenarios, the total amount of carbon surplus of baseline scenario was the highest, and scenario C was the lowest (Figs. 5, 6 and 7).

The dense carbon sink ($>2.0 \times 10^5 \text{ g m}^{-2}$) areas concentrated in the Qinling Mountains, while the low carbon sink ($<2.0 \times 10^5 \text{ g m}^{-2}$) areas concentrated in the Guanzhong Plain. The total carbon sinks of Qinling Mountains (DEM > 1200 m) in all scenarios are 7.41×10^9 to 7.45×10^9 t, accounts for 49.41% (baseline), 48.35%

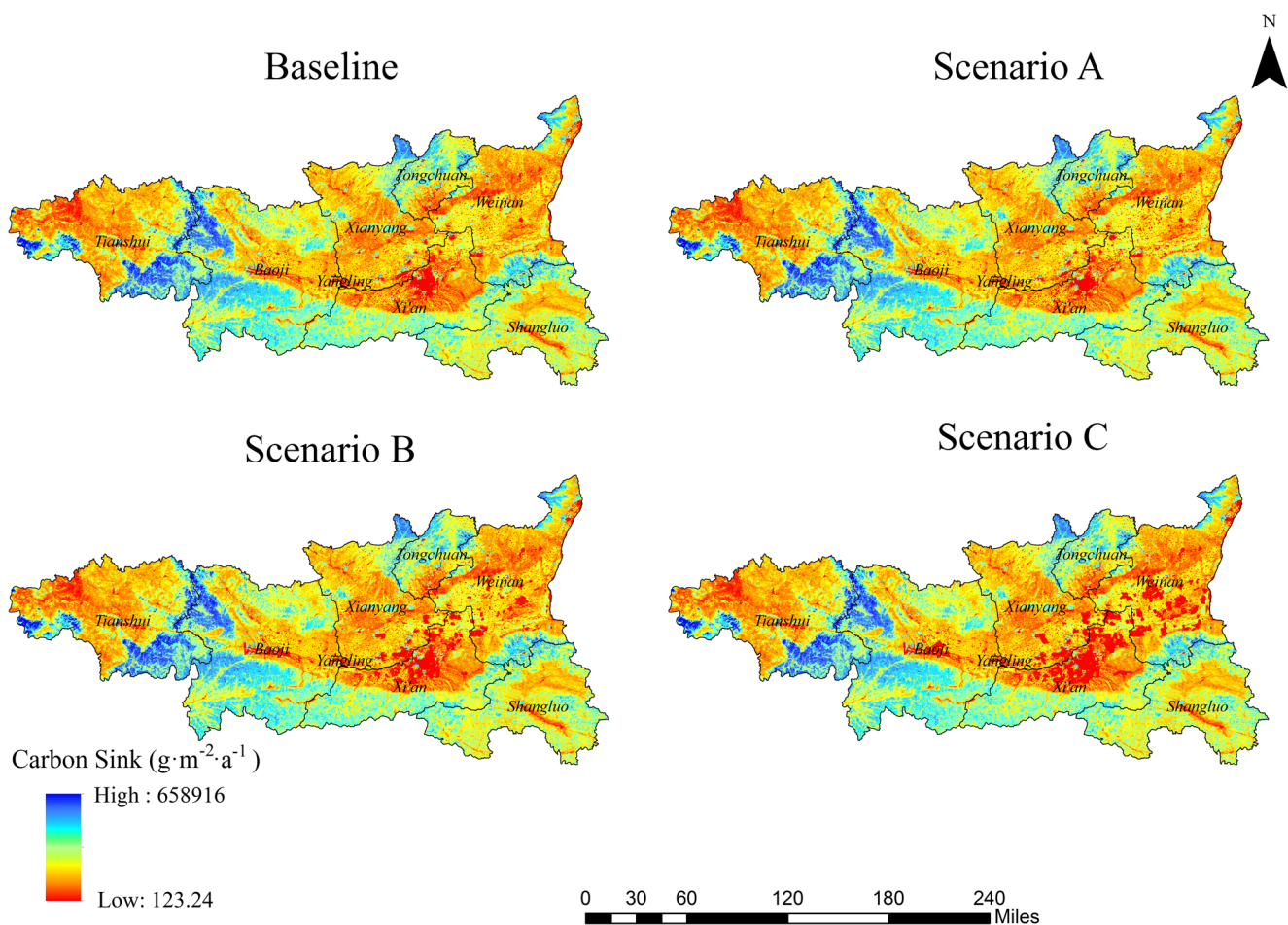


Fig. 5 Maps of carbon sink for baseline, scenario A, scenario B, and scenario C

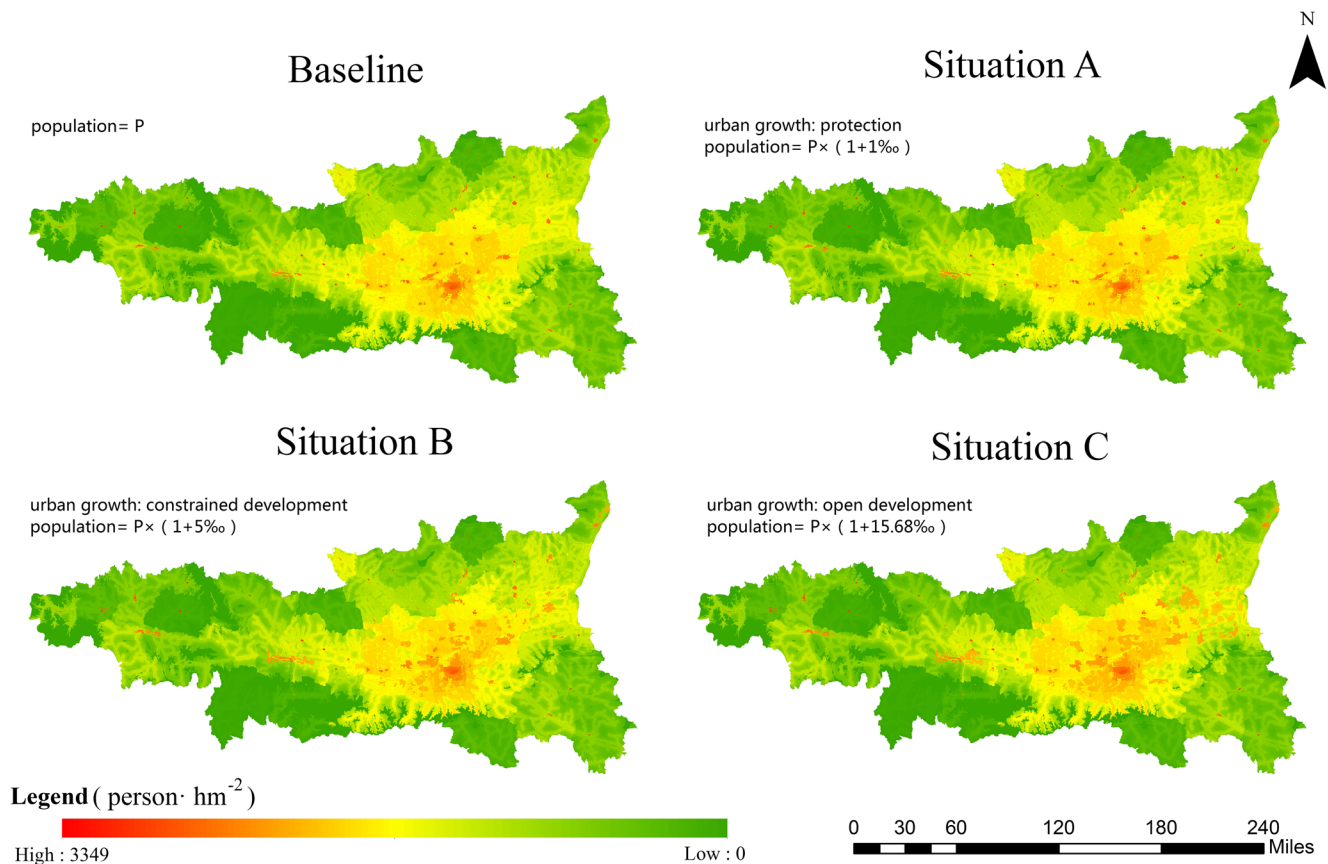


Fig. 6 Maps of population density for baseline, scenario A, scenario B, and scenario C

(scenario A), 48.43% (scenario B), and 48.19% (scenario C) of GTER, respectively. The total carbon sinks of Guanzhong Plain (DEM < 800 m) in all scenarios are 2.59×10^9 to 2.96×10^9 t, accounts for 19.63% (baseline), 19.25% (scenario A), 18.36% (scenario B), and 16.76% (scenario C) of GTER, respectively.

The land use and social economic change in GTER by 2050 will have a considerable impact on carbon budget. However, the influence depends critically on the urban growth and forest cover rate. Taking Xi'an City as an example, carbon budgets in the three future scenarios have obvious differences. The data in the following analysis are all relative to baseline. In scenario A, the urban growth of Xi'an City is strictly controlled, and its afforestation is improved effectively. What is more, its grassland and unused land are fully utilized. As results, its urban area decreases 9.28%, forest cover rate increases 11.50%, and farmland cover increases 4.87%. Accompanying these changes of land use, the carbon sink of Xi'an City increases 1.40%, carbon source decreases 38.08%, and carbon surplus increases 1.41%. In scenario B, the urban area of Xi'an increases 37.68%, forest cover rate decreases 6.17%, and farmland cover decreases 5.10%. Although the carbon emission per capita decreases 24.42% (from 2.17 to 1.64 t C), carbon source only decreases 14.47%. And the

decrease of forest and farmland results in a considerable decrement (6.47%) of carbon sink. The carbon surplus of scenario B decreases 6.51%. In scenario C, free market forces across all parts of the landscape, and urbanized area expands rapidly. As results, its urban area increases 89.44%, forest cover rate decreases 6.62%, and farmland cover decreases 21.98%. Accompanying these changes of land use, the carbon sink of Xi'an City decreases 15.87%, carbon source increases 21.98%, and carbon surplus decreases 15.99%. However, for GTER as a whole, these changes have a considerable impact on carbon source, but not on carbon sink. Compared with baseline, the carbon source of GTER decreases 55.37% (scenario A), 14.29% (scenario B), and -23.06% (scenario C), respectively, while carbon sink decreases 0.43% (scenario A), 0.83% (scenario B), and 2.43% (scenario C), respectively.

Economic values of carbon budget

Changing carbon price and discount rate in GTER by 2050 could affect NPV of carbon budget obviously. In the three future scenarios, the carbon budget NPV of scenario A is the highest (1.52×10^{12} RMB); it is 1.91 times of scenario B (7.97×10^{11} RMB) and 4.75 times of scenario C (3.20×10^{11} RMB) (Fig. 8).

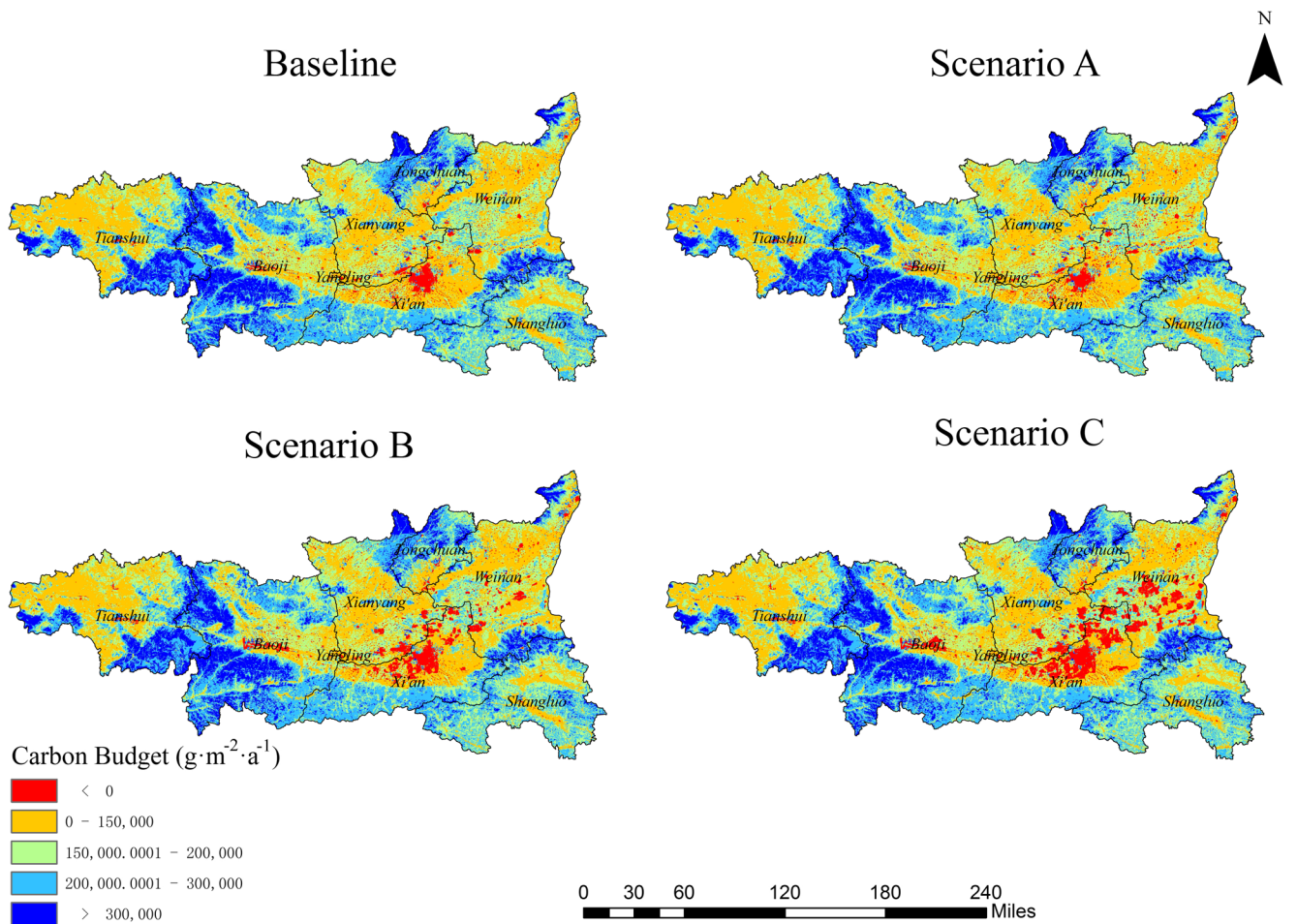
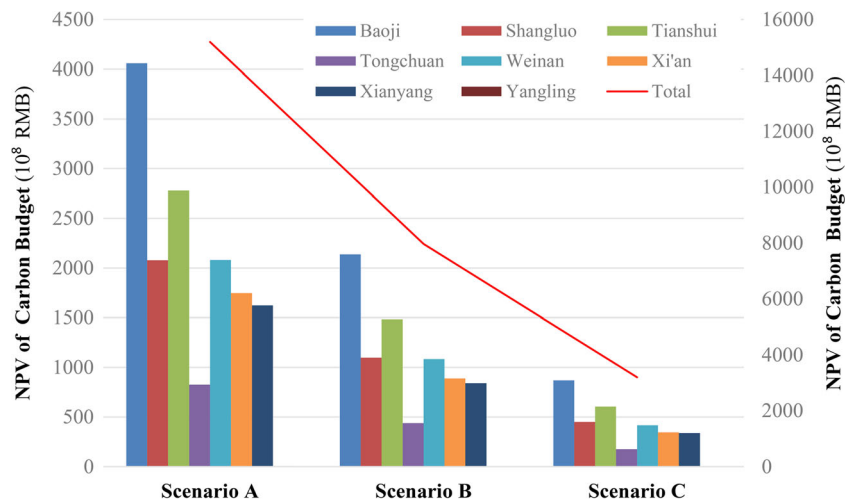


Fig. 7 Maps of carbon budgets for baseline, scenario A, scenario B, and scenario C

The high carbon sink areas were found more sensitive to changes in carbon price and discount rate. As the comparatively highest carbon sink area, Baoji is the most sensitive area. Its carbon surplus NPV in scenario A is 4.06×10^{11} RMB, which is 1.92×10^{11} RMB higher than scenario B

and 3.19×10^{11} RMB higher than scenario C. Carbon surplus NPV of Tianshui in scenario A is 2.78×10^{11} RMB, which is 1.30×10^{11} RMB higher than scenario B and 2.17×10^{11} RMB higher than scenario C, respectively. However, carbon surplus NPV of Yangling in scenario A is 9.13×10^8 RMB,

Fig. 8 NPV of carbon budget in scenario A, scenario B, and scenario C



which is only 4.37×10^8 RMB higher than scenario B and 7.27×10^8 RMB higher than scenario C, respectively.

In the best ecological environment management (scenario A), Baoji’s carbon surplus of NPV can reach 4.06×10^{11} RMB; even in the relaxed ecological management, the carbon surplus of NPV still can reach 8.69×10^{10} RMB (Fig. 9). In Baoji and its subordinate administrative region, the carbon source of Fengxiang County is the minimum, and the carbon surplus is the maximum; its NPV is more than 8×10^{10} RMB in scenario A. Jintai District of Baoji City, Fengxiang County of Baoji, Taibai County of Baoji, and Zhashui County of Shangluo are the typical regions of “high sink and low source.” The carbon balance in Beilin District, Lianhu District, and Xincheng District of Xi’an City is negative. These areas’ deficit of NPV is 5.37×10^7 RMB, 5.39×10^7 RMB, and 4.03×10^7 RMB. In addition to Changan District and Lintong District, in the other urban areas of Xi’an, the surplus of NPV is not more than 3.8×10^9 RMB in the scenario A. Xi’an and Xianyang are typical regions of “high source and low carbon sink.” Pucheng County of Weinan, Qian County of Xianyang, Linwei District of Weinan, Wugong County of Xi’an, and Beilin District, Lianhu District, and Xincheng District of Xi’an City are the typical areas of “low sink and high source.” Meiji District of Tianshui, Chengcang District of Baoji, Shangzhou District of Shangluo, and Zhouzhi County of Xi’an are typical regions of “high sink and high source.” The smaller area region of Wangyi District of Tongchuan, Tongguan County of Weinan, and Yangling District are the typical region of “low sink and low source.”

Discussion

Mapping and evaluating ecosystem services can result in spatial and economic references for policy decision makers. This study established multiple scenarios, using the CASA model, carbon recycling process model, spatially defined population densities, and NPV approach to estimate carbon budgets for 2014 and to predict future conditions. Urban growth, climate change, population growth, carbon emission per capita, and carbon markets were chosen as the five factors influencing the scenarios.

Carbon budgets differ for many reasons: climate change, land use type, and carbon emission per capita. High temperatures negatively impact terrestrial carbon sequestration; in the face of ongoing global warming, carbon sink is likely to continue to be reduced in future decades. Carbon sink in GTER mainly relies on the Qin Mountains, where forest density is the highest. This implies that protecting the Qinling Mountains is essential to maintain the region’s carbon balance. Urban expansion is one driver of carbon deficits; in scenario C, significant urbanization combined with population growth and excess resource consumption resulted in carbon deficits across almost the entire Guanzhong Plain.

Carbon budgets and land use change

In the six land types of this study, forests sequester the largest amount of carbon for both unit area and total amount. This means that the Qinling Mountains and surroundings are the

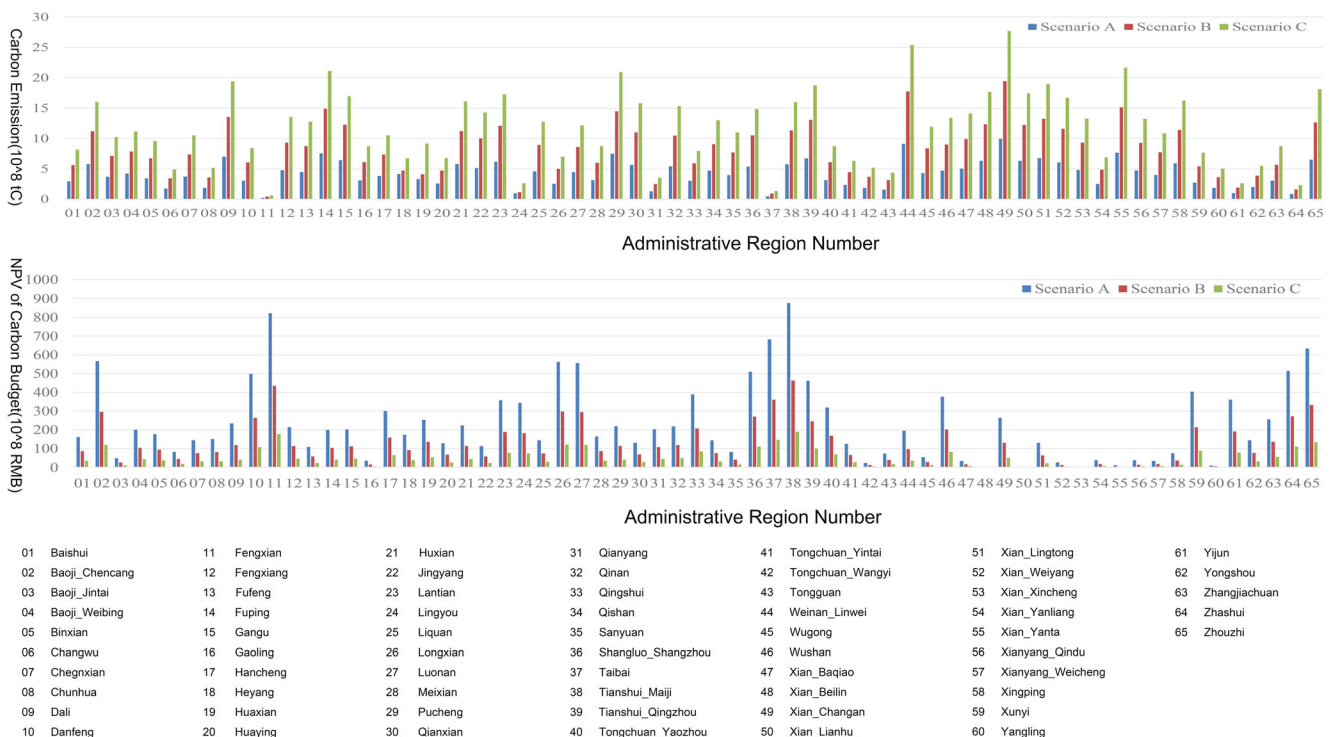


Fig. 9 Carbon source and the NPV of each district in scenario A, scenario B, and scenario C

largest carbon sink in GTER. Croplands are not the second largest carbon sink for unit area, but the second largest carbon sink for total, because of its huge area. The carbon budgets for unit area of grasslands are 3.43–3.77 t higher than croplands, but the total amount of it is lower than cropland. Urban area is the only carbon deficits in all six land types. High carbon source, combined with low carbon sink level, leads to high carbon source in the city area, exceeding sink.

Land use has a considerable impact on carbon budgets. In the scenario A, the expansion of the sprawling metropolis is strictly restricted, and returning farmland to forest (grass) project is encouraged; these measures make the carbon budget about 3.75×10^7 t. In the scenario B, the expansion demand of the cities and industries in Guanzhong Plain is stronger; at the same time, the occupation of croplands is restricted, in which land use policy makes the carbon budgets decreased about 1.21×10^8 t. In the scenario C, the development of the sprawling metropolis requires huge urban expansion, carbon source increases sharply, and carbon budgets decreased about 3.91×10^8 t.

As a key ecological protection area, the establishment of national forest parks and national geological parks in Qinling Mountains makes the primary forest well protected. At the same time, the returning farmland to forest (grass) project had been playing a promoting role in ecological protection since 2003. Therefore, the carbon budget of GTER maintains a surplus in all of the scenarios in this study. However, in the Guanzhong Plain, which is dense with people, industry, and expanding cities, carbon deficit area will increase sharply if there is no scientific policy to limit urban expansion.

Carbon budgets and social economy

From the point of view of social justice, the carbon surplus of one area can be transferred to the carbon deficit country or districts in paid way. And in most conditions, these transfers of carbon emission rights have to be achieved at the expense of economic benefits.

Since the first Assessment Report of the IPCC linked human greenhouse gas emissions to global warming (1990), new policies to reduce carbon emission are constantly being raised. As the representative of developed countries, Denmark and Holland adopted strict carbon tax policies to carbon dioxide products and services (Kerkhof et al. 2008; Sovacool 2013). China, as a developing country, approved a series of pilot cities/provinces of carbon emissions trading: Beijing, Tianjin, Shanghai, Chongqing, Shenzhen, Guangdong Province, and Hubei Province in 2013. This may be a signal that China is starting to levy a carbon tax in the future. In this study, we assessed the NPV of carbon budgets under different social economic scenarios.

Population aging and population negative growth follow the strict family planning. Carbon emission is strictly

controlled through energy policy, such as the purchase of high carbon emission products or services has to pay high carbon taxes.

Good ecological resource management can not only maintain and even restore the biodiversity of the region and increase carbon sink but also increase the carbon surplus of NPV. Compared with lax policies, carbon emissions need to pay a much higher price under the strict ecological management policy. Driven by net profit, the company's policy makers are more inclined to choose renewable resources and energy-saving emission reduction measures, rather than pay an expensive environmental tax. As a result of strict family planning policy and discarding the concept of "more happiness comes with more offsprings," Chinese population enters a stage of aging and reduction. With the summation of human being's demand on resource and service decreased, the consumption of social resource and energy has decreased and further promotes the reduction of carbon emissions.

In scenario C, such as urban expansion, population explosion, and rising energy demand, these factors make the consumption of life energy soar. In pursuit of economic growth, the government allows companies to emit carbon dioxide at a very low economic cost. The total carbon surplus of NPV in the study area is only 3.20×10^{11} RMB, which is about one fifth of the scenario A. The simply pursuit of ecological environmental protection or economic growth is not the best choice for decision makers. Decision makers need to weigh the pros and cons, looking for a suitable state between the two. In this study, scenario B is studied and discussed as an intermediate state.

Methodological issues associated with the integration of agent-based approaches and ecosystem models

(Attempt and advantages) GTER is an important development area of Northwest China. Several researchers have estimated carbon sources and sinks in this area using different models.

Carbon sequestration in the Shaanxi section of the Han River was estimated using InVEST; this ecosystem service was valued by substituting the market method at 6.07×1.0^{11} RMB (Wei et al. 2014). Carbon sequestration in GTER was estimated using the CASA model; the economic value of the sequestered carbon was calculated using the reforestation cost approach. A study showed that the carbon sequestration per unit area in 2007 was $2.821 \text{ t CO}_2 \text{ hm}^{-2} \text{ a}^{-1}$, with an economic value of 2.16×10^{11} RMB a^{-1} (Zhou et al. 2013). Carbon source (combined vegetation) and the carbon footprint of Shaanxi were evaluated based on the guidelines of the IPCC; the 2009 carbon source level and carbon footprint were identified as 3.55×10^9 and $2.60 \times 10^8 \text{ t C}$, respectively (Zhao et al. 2013). A study in the Guanzhong area using a CASA model and agricultural carbon emission formula showed carbon sources and sinks of the

agroecosystem using 2010 data, calculating source and sink as 6.44×10^4 and 1.41×10^6 t CO₂, respectively (Wei et al. 2014). The experience method and market value approach were used to evaluate carbon sequestration in the Shaanxi forest ecological system, revealing a sequestration payment of 3.28×10^{10} RMB (Ma et al. 2010).

The abovementioned studies assessed the carbon source/sink or payment of the Shaanxi or Guanzhong areas from various perspectives; however, they did not take into account the combined effects of climate, land use, and social economy changes (different carbon prices and discount rates). Carbon sink payment at the baseline (2014) was at least 3.20×10^{11} RMB and may reach up to 1.52×10^{12} RMB.

This study established multiple scenarios (climate, land use, and social economic changes) to measure carbon sink (aboveground and belowground) in GTER using remote sensing and a process model. Population density was introduced to account for carbon sources caused by human beings. Using these variables, carbon budgets for the four scenarios were evaluated for the region using NPV; carbon budgets under the different scenarios were analyzed to provide references for regional carbon accounting.

(Uncertainties and limitations) Compared with statistical data, this study increased spatial resolution. However, combining multiple models also increases the uncertainty of the results. Precipitation, air temperature, solar radiation, and remote sensing data products were used in combination, with multiple parameters involved. These methods may limit the accuracy of estimates to a certain extent. The assumptions about future such as land use changes, carbon prices, and discount rate may have certain gaps with the real values in the future, which also increase the uncertainties of results.

In the CASA model, parts of the parameters related to the amount of photosynthetically active radiation (APAR) are based on empirical values. If these parameters were measured data instead, NPP results may be closer to reality. The interpretation of mixed pixels (forestland and farmland, woodland, and grassland) in remote sensing images may also limit the exactness of calculations. For the SOC estimate, the result can be verified through field sampling and soil analyses. More effective verification would increase precision.

In addition to carbon sinks and sources, carbon markets influence carbon budgets. The discount rate represents the weight of future funds. The higher the discount rate, the more emphasis of current people on the welfare of future generations. When studying soil carbon payment estimates, the rate reflects a contemporary valuation of future generational interests. Higher discount rates indicate that more people put emphasis on the interests of future generations. Against the background of the current social economy, it is difficult to predict the exact parameters of future economic development. For example, the estimated carbon prices and discount rates may differ from actual future NPV. Factors such as soil erosion,

slope, and elevation should also be included in the model. Population policies must also be accounted for when considering future development.

Conclusion

Ecological factors (e.g., climate change) have been embedded in decision-making, and human activities (e.g., LUCC and economic development) also attracted more and more attention of ecologists. To clarify mechanisms related to the terrestrial ecosystem carbon cycle and its outside pressures (ecological and social), a more comprehensive model that embed both ecological and social factors is needed.

The study considered the effects of five factors on carbon sink and source: urban growth, climate change, population growth, carbon emission per capita, and carbon market. Deforestation, urban sprawl, population explosions, and an excess carbon consumption are primary challenges in balancing carbon source and sink. Carbon price and discount rate positively impact the NPV of carbon budget. In this sense, increasing carbon subsidies may encourage excess carbon consumption.

Mapping and valuing carbon budget still face theoretical and methodological challenges. Future research should focus on increasing the number of studied scenarios and including model factors such as soil erosion slope and elevation impact factors. And how to define the area of carbon source, carbon sink, and carbon use is also a research priority in this field.

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