Distribution characteristics and prediction model of farmland soil organic carbon in eastern China

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Abstract

Soil organic carbon (SOC) plays a key role in soil improvement, carbon sequestration, and increasing crop yield. In this study, the distribution characteristics and the influence of hydrothermal conditions on farmland SOC content in eastern China were studied. The results showed that the spatial heterogeneity of SOC content in eastern China was obvious. In the area with the mean average temperature (MAT) below 10.42 °C, the SOC content was negatively correlated with MAT and ≥10 °C accumulated temperature, but positively correlated with the ratio of precipitation to temperature (P/T). In the area with the MAT between 10.42 °C and 20.75 °C, the SOC content was negatively correlated with mean average precipitation (MAP), MAT, P/T and ≥10 °C accumulated temperature. In the area with the MAT above 20.75 °C, the SOC content was negatively correlated with MAT and ≥10 °C accumulated temperature, but positively correlated with MAP and P/T. In the area with the MAP below 400 mm, the SOC content was negatively correlated with P/T, but positively correlated with MAP, MAT and ≥10 °C accumulated temperature. In the area with the MAP between 400 mm and 800 mm, the SOC content was negatively correlated with MAT, but positively correlated with MAT and ≥10 °C accumulated temperature. In the area with the MAP more than 800 mm, the SOC content was negatively correlated with MAP, MAT, P/T and ≥10 °C accumulated temperature. Based on the above results, a model for predicting SOC content was established. This is of great significance for the rapid estimation of SOC content on a regional large scale.

1. Introduction

As one of the main terrestrial carbon pools, soil organic carbon pools (SOCP) plays a key role in the global carbon cycle (Nave et al 2018, Diel and Franko 2020), which is two to three-fold higher than the vegetative and atmosphere carbon (Zissimos et al 2019). Soil organic carbon (SOC) is a form of carbon in soil organic compounds. It is of great significance to study the spatial distribution characteristics and influencing factors of SOC in response to current climate change and soil sustainable management. There are many factors that affect the content of SOC, including climate, soil physical and chemical properties (such as soil parent material) and human (such as fertilization) (Schillici et al 2017, Tziachris et al 2019, Zhuo et al 2022). Generally speaking, climate is generally considered to be the dominant factor driving soil carbon dynamics. On a larger scale, most of the changes in SOC are driven by climatic conditions (Wang et al 2019). Especially for topsoil, climate directly or indirectly regulates the change of SOC content through different hydrothermal relationships. Temperature can
achieve control of the change rate of SOC by affecting the activity of microorganisms in soil. Higher temperature can speed up the process of physical and chemical reaction in soil, motivate microbial activity, promote metabolism and boost the crop growth rate (Koven et al 2017). Therefore, the decomposition rate of SOC and soil nutrients is also accelerated, resulting in the decrease of their content (Gao et al 2020). On the contrary, SOC is easier to accumulate. Precipitation will directly affect soil moisture, soil aeration and soil redox process to a great extent. Soil moisture is an indispensable condition for the maintenance of soil microbial activity, soil mineral weathering, and the synthesis and decomposition of organic matter. Therefore, precipitation can directly affect SOC content (Cui et al 2019, Felton et al 2020). Some scholars believed that the degree of explanation of the temperature to the SOC was much greater than the precipitation, and the SOC decomposition rate was indexed with the temperature (Wang et al 2019, Chen et al 2020). However, there were also studies proposing that the interaction between temperature and precipitation provided the adequate explanation for the spatial heterogeneity of SOC density (Guanlin et al 2017, Tian et al 2020). On the regional scale, microbial carbon, nitrogen and phosphorus limits are often determined by climatic factors (hydrothermal conditions). The impact of temperature and precipitation on the microbial metabolic process strongly restricts the stability of SOC (Zheng et al 2021).

At present, people are more and more interested in studying the temporal and spatial pattern of SOC reserves as well as quantifying the SOC storage potential (Launay et al 2021, Xie et al 2021). Many research data on soil quality change come from farmland quality monitoring data, sampling data and published literature data. On a regional or national scale, GIS spatial analysis method, geostatistical method and digital soil mapping method are often used to study the temporal and spatial changes of farmland soil organic carbon (Zhao et al 2021, Zhuo et al 2022). At the same time, some new methods or models are gradually applied to evaluate the dynamic changes and driving forces of regional SOC. For instance, Li et al (2022) used a machine learning approach to study the dynamic changes of organic carbon in different soil layers in China, and found that climate change was the dominant influencing factor. Qiu et al (2021) simulated the spatial pattern of soil carbon density in China based on earth system model and found that the overall simulation effect was good, but there were great differences in the simulation of regional average soil carbon density.

Affected by the East Asian summer monsoon, the precipitation in eastern China is extremely uneven in time and space, and the hydrothermal conditions are complex (Wei et al 2021). Water vapour from low latitude easily increases the surface latent heat flux, which affects the change of SOC content (Södergren et al 2018). In 2020, China clearly put forward the goal of ‘carbon emission peaking and carbon neutrality’. Under this climate condition and carbon reduction background, studying the distribution characteristics of farmland SOC in eastern China is conducive to clarifying the regional soil carbon sequestration potential and can provide a scientific basis for soil quality management. In addition, it is very difficult to quantitatively predict the change of SOC under the changeable environment, especially when the distribution of soil sampling points is sparse and inconsistent with time (Minasny et al 2013, Meng et al 2020). Even though the digital soil mapping method can realize the comparison and prediction of large-scale SOC change (Lamichhane et al 2019), there are also some shortcomings, such as many model parameters, slow inversion process and difficulty in verifying the model. Therefore, it is necessary to explore a fast, effective SOC prediction model with few input parameters.

Based on the SOC data of Soil Testing and Formula Fertilization Basic Nutrients Data Set and the meteorological data of Meteorological Science Data Sharing Service Network, the internal relationships between SOC content and temperature and precipitation on a regional scale were analysed in this study. It defined the macro dominant factors of SOC distribution pattern, and further put forward a model for predicting SOC based on hydrothermal conditions. It was expected to provide scientific reference for adjusting farmland soil management policies, promoting soil carbon fixation and reducing carbon loss in eastern China.

2. Materials and methods

2.1. Study site
This study covered 13 provinces or municipalities in eastern China, including Heilongjiang Province, Jilin Province, Liaoning Province, Beijing City, Tianjin city, Hebei Province, Shandong Province, Jiangsu Province, Shanghai City, Zhejiang Province, Fujian Province, Guangdong Province and Hainan Province. The main soil types in each study area were shown in table 1, and the distribution of sample points was shown in figure 1.

2.2. Data sources
China has implemented the national soil testing and formula fertilization project since 2005. Although the soil test time was different from place to place, most of the tests were completed between 2008 and 2010. At that time, the soil was sampled based on the county area, which was evenly obtained in the space, with farmland as sample land use type, and the sampling depth was 0 ~ 20 cm (topsoil). In 2014, China Agricultural Technology
Extension Service Centre summarized the data of all sampling points and compiled the ‘Soil Testing and Formula Fertilization Basic Nutrients Data Set (2005–2014)’. It included soil organic matter (SOM), total nitrogen, available phosphorus, available potassium and pH, and reflected the average level of each county in this period. In this study, the SOM data of eastern China were selected from the data set, a total of 752 sample points were obtained, and the GPS coordinates of the county-level administrative centre were used as the geographical coordinates of the sample points. Finally, the SOC content of the sample point was obtained by multiplying SOM by 0.58.

Based on national basic meteorological observatory, the meteorological data was borrowed from China Meteorological Science Data Sharing Service Network (http://data.cma.cn). Considering that the above SOC content data was the average state in a specific period, this study took the mean average temperature (MAT), mean average precipitation (MAP), ≥10 °C accumulated temperature and the ratio of precipitation to temperature (P/T) as the meteorological data indicators. In order to reduce the interference of climate abnormal years on the results, this study appropriately extended the time series of meteorological data, selected the meteorological data of counties in eastern China from 2000 to 2016, and matched the average value with the SOC content data.
Table 2. SOC prediction model building process.

| Step | Operation program | Explanation |
|------|-------------------|-------------|
| 1    | Begin             | Input data: explanatory variable data set $T(x_i, y)$ and explained variable $y$. |
| 2    | $T' = (x'_1, x'_2, \ldots, x'_k)$ ← PCA($T, y$) | Data dimensionality reduction by PCA method. |
| 3    | $i = 1$           | Initialize the index of variable $x$. |
| 4    | For $x_i$ in $T'$ $(x'_1, x'_2, \ldots, x'_k)$ | Cycle each set of variables $x$. |
| 5    | $p_i$ ← Pearson $(x_i, y)$ | Calculate Pearson correlation coefficient between each group of variables $x$ and $y$. |
| 6    | $i = i + 1$      | The index value of each cycle plus 1. |
| 7    | $P ← (\{x'_1, p_1\}, \{x'_2, p_2\}, \ldots, \{x'_i, p_i\})$ | The index of each group of variable $x$ after dimensionality reduction and the corresponding Pearson correlation coefficient were stored in $P$. |
| 8    | $(x''_1, x''_2, \ldots, x''_n)$ ← sorted $(P, \text{key} = 'p_i')[0:m]$ | Sort the Pearson correlation coefficients of each group of variable $x$, and take out the $m$ groups of variable $x$ with the highest Pearson correlation coefficient for modeling. |
| 9    | $T'' ← (x''_1, x''_2, \ldots, x''_n)$ | Save the $m$ groups of variable $x$ with the highest Pearson correlation as data set $T''$. |
| 10   | $F(x) ← \text{Linear Regression}(T'', y)$ | Construct multiple regression model $F(x)$ according to training data set $T''$. |
| 11   | End               | Output the mathematical expression of $F(x)$. |

2.3. Data analysis

Ordinary Kriging (OK) is a linear unbiased optimal estimation based on semi-variogram theory and structural analysis (Arslan 2012, Liu et al. 2021). The semi-variogram formula is as follows:

$$\gamma_h = \frac{1}{2n} \sum_{i=1}^{n} [Z(x_i) - Z(x_i + h)]^2$$  \hspace{1cm} (1)

Where, $\gamma_h$ is the semi-variance value for all pairs at a lag distance $h$; $n$ represents the number of pairs of observations separated by the distance $h$, $Z(x_i)$ is the measured value of the variable at point $x_i$, $Z(x_i + h)$ is the measured value of the variable at point $x_i + h$. In this study, OK was used to obtain the spatial distribution characteristics of SOC content, which was implemented in the geostatistics tool of ArcGIS 10.5 software.

Principal component analysis (PCA) is a technique to reduce the number of variables and eliminate the relations among input variables (Guo et al. 2018). More details on PCA can be found in the work of Abdi and Williams (2010), which provided a good overview. Before modeling, the principal components were determined by observing the PCA results (eigenvalues and cumulative contribution rates) in this study. The specific modelling process was shown in Table 2. Data processing was implemented in SPSS 22.0 and Matlab 2016 software.

Verification and evaluation of SOC prediction model: 70% of the research data were used to establish SOC prediction model and the remaining 30% of the research data were used to verify the accuracy of the model. The mean error (ME), mean absolute error (MAE), and root mean squared error (RMSE) were calculated to evaluate the difference between the estimated and measured values. These formulas are as follows:

$$\text{ME} = \frac{1}{N} \sum_{i=1}^{N} [S(x_i) - (T_i)]$$  \hspace{1cm} (2)

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} [|S(x_i) - (T_i)|]$$  \hspace{1cm} (3)

$$\text{RMSE} = \frac{1}{N} \sqrt{\sum_{i=1}^{N} [(x_i) - (T_i)]^2}$$  \hspace{1cm} (4)

Where, $N$ is the number of verification points, $S(x_i)$ is the measured value of the variable at point $x_i$, $T(x_i)$ is the estimated value of the variable at point $x_i$.

3. Results

3.1. Distribution pattern of SOC content in eastern China

As shown in figure 2, there was obvious spatial heterogeneity in the content of SOC in each province or municipality.

The soil formed in the cold climate of Northeast China had a deep humus layer, with mostly black and meadow soil types and generally high SOC content. The content of SOC in Heilongjiang Province was
13.80 ~ 26.09 g·kg\(^{-1}\), with an average of 20.74 g·kg\(^{-1}\). The high-value zone was located in the east and the northwest, and the southwest was lower; the content of SOC in Jilin Province was 8.17 ~ 32.01 g·kg\(^{-1}\), with an average of 16.63 g·kg\(^{-1}\), showing a decreasing trend from southeast to northwest; the content of SOC in Liaoning Province was 7.21 ~ 16.51 g·kg\(^{-1}\), with an average of 10.41 g·kg\(^{-1}\), showing a decreasing trend from east to west.

Due to the limitation of water, the net primary productivity in North China was low, the soil type was mainly cinnamon soil, and the SOC content was generally low. The content of SOC in Hebei Province was 6.27 ~ 12.67 g·kg\(^{-1}\), with an average of 10.02 g·kg\(^{-1}\). The high-value zone was located in the north and the west, and the southeast was lower; the content of SOC in Beijing City was 7.05 ~ 10.31 g·kg\(^{-1}\), with an average of 8.44 g·kg\(^{-1}\). The low-value zone was smaller; the content of SOC in Tianjin City was 7.76 ~ 11.55 g·kg\(^{-1}\), with an average of 10.28 g·kg\(^{-1}\). The high-value zones were mainly distributed in the central and the western regions.

There were various soil types in East China. The strong chemical weathering and eluviation led to faster turnover rates of SOC and obvious space differences in this area. The content of SOC in Shandong Province was 5.83 ~ 10.24 g·kg\(^{-1}\), with an average of 10.02 g·kg\(^{-1}\). The high-value zone was mainly distributed in the central region; The content of SOC in Jiangsu Province was 9.36 ~ 17.74 g·kg\(^{-1}\), with an average of 12.34 g·kg\(^{-1}\), showing a decreasing trend from southwest to northeast; the content of SOC in Zhejiang Province was 14.21 ~ 17.80 g·kg\(^{-1}\), with an average of 15.95 g·kg\(^{-1}\). The high-value zone was mainly distributed in the east coastal area; the content of SOC in Fujian Province was 13.13 ~ 17.19 g·kg\(^{-1}\), with an average of 15.84 g·kg\(^{-1}\), showing a decreasing trend from west to east.

The main soil type in Southern China was red soil. Due to the low latitude and high temperature, red soil was not conducive to the accumulation of SOC, resulting in the SOC content at a medium level. The content of SOC in Guangdong Province was 10.94 ~ 17.44 g·kg\(^{-1}\), with an average of 14.15 g·kg\(^{-1}\). The low-value zones were mainly distributed in the southwest and southeast; the content of SOC in Hainan Province was 3.69 ~ 14.97 g·kg\(^{-1}\), with an average of 9.83 g·kg\(^{-1}\), showing a decreasing trend from northeast to southwest.

### 3.2. Effects of hydrothermal conditions on SOC content distribution pattern

#### 3.2.1. Temperature

The relationship between SOC content and MAT was a cubic curve. The formula was \[ y = -0.0108x^3 + 0.5032x^2 - 6.9794x + 39.1888, (r = 0.7374, P < 0.01) \]. It reached the bottom of the curve at about 10 °C and the high point at about 21 °C (figure 3). Through the derivative, the curve breaks were 10.42 °C and 20.75 °C respectively. Accordingly, the relationship between SOC content and hydrothermal conditions was studied in the temperature ranging from <10.42 °C, 10.42 °C ~ 20.75 °C and >20.75 °C.

As shown in table 3, in the area with the MAT below 10.42 °C, the SOC content was significantly negatively correlated with MAT (\( r = -0.7357, P < 0.01 \)) and ≥10 °C accumulated temperature (\( r = -0.7467, P < 0.01 \)).
but positively correlated with $P/T$ ($r = 0.7934$, $P < 0.01$). There was no significant correlation between SOC content and MAP. Therefore, temperature was the dominant factor affecting SOC content under this condition.

In the area with the MAT between 10.42°C and 20.75°C, the SOC content was significantly negatively correlated with MAP ($r = -0.8039$, $P < 0.01$), MAT ($r = -0.8341$, $P < 0.01$), $P/T$ ($r = -0.7724$, $P < 0.01$) and $\geq 10^°$C accumulated temperature ($r = -0.8293$, $P < 0.01$). It could be seen that temperature and precipitation had a synergistic effect on the distribution of SOC content, both of which played a negative role. The correlation between SOC content and MAT was higher than that between SOC content and MAP, which showed that the temperature contributed more to the accumulation of SOC.

In the area with the MAT above 20.75°C, the SOC content was significantly negatively correlated with MAT ($r = -0.5690$, $P < 0.01$) and $\geq 10^°$C accumulated temperature ($r = -0.6701$, $P < 0.01$), but positively correlated with MAP ($r = 0.4517$, $P < 0.05$) and $P/T$ ($r = 0.4471$, $P < 0.05$). Accordingly, temperature was still the main factor affecting SOC content, followed by precipitation. The synergistic effect of hydrothermal conditions on SOC content was weak. And $\geq 10^°$C accumulated temperature had more obvious negative correlation with SOC content than MAT had.

### 3.2.2. Precipitation

According to the division standard of dry and wet areas in China, the study area was divided into three different precipitation areas, with MAP of $<400$ mm, 400 mm $\sim$ 800 mm and $>800$ mm respectively (table 4).

In the area with the MAP below 400 mm, the SOC content was significantly negatively correlated with $P/T$ ($r = -0.9031$, $P < 0.01$), but positively correlated with MAP ($r = 0.6922$, $P < 0.01$), MAT ($r = 0.8908$, $P < 0.01$) and $\geq 10^°$C accumulated temperature ($r = 0.8808$, $P < 0.01$). The correlation between SOC content and $P/T$ was the best, which indicated that the synergistic effect of hydrothermal conditions played an important role in SOC accumulation.

In the area with the MAP between 400 mm and 800 mm, the SOC content was significantly negatively correlated with $P/T$ ($r = -0.8233$, $P < 0.01$), but positively correlated with MAT ($r = 0.8576$, $P < 0.01$) and $\geq 10^°$C accumulated temperature ($r = 0.8731$, $P < 0.01$). There was no significant correlation between SOC and MAP. So, temperature was still the main factor affecting SOC content and played a positive role.

In the area with the MAP more than 800 mm, the SOC content was significantly negatively correlated with MAP ($r = -0.3841$, $P < 0.01$), MAT ($r = -0.6921$, $P < 0.01$), $P/T$ ($r = -0.5557$, $P < 0.05$) and $\geq 10^°$C accumulated temperature ($r = -0.6099$, $P < 0.05$). The spatial distribution of precipitation in Northeast China was gradually decreasing from southeast to northwest. Affected by the East Asian monsoon and topography, some cities in the east of Changbai Mountain were located on their windward slope, with more topographic rain, and the precipitation was far higher than that near the same latitude (Du et al 2013). These cities mainly include Helong City, Fusong County, Liniang City, Jiangyuan County, Tonghua County, Ji’an City in Jilin Province, and Huanren Manchu Autonomous County, Kuandian Manchu Autonomous County, Donggang City, Fengcheng City, Zhenxing District and Zhen’an District in Liaoning Province. It was found that except $P/T$, the correlation between SOC content and other factors became better after removing the above 12 areas. After the removal, the SOC content was significantly negatively correlated with MAP ($r = -0.5782$, $P < 0.01$), MAT ($r = -0.6933$, $P < 0.01$), $P/T$ ($r = -0.5172$, $P < 0.05$) and $\geq 10^°$C accumulated temperature ($r = -0.7058$, $P < 0.01$). Followed by precipitation, temperature was still the main factor affecting SOC content.

\begin{equation}
y = -0.0108x^3 + 0.5032x^2 - 6.9794x + 39.1888
\end{equation}

\begin{equation}
r = 0.7374, P<0.01, n = 752
\end{equation}

Figure 3. Relationship between SOC content and MAT.
Table 3. Relationship between SOC content and hydrothermal conditions in different MAT areas.

| MAT areas                           | <10.42 °C | 10.42 °C ~ 20.75 °C | >20.75 °C |
|-------------------------------------|-----------|---------------------|-----------|
| Heilongjiang Province, Jilin Province, Liaoning Province, Northern part of Hebei Province | 166       | 481                 | 85        |
| Number of samples                   |           |                     |           |
| $y=2E-08x^2-3E-05x^2+0.0367x+5.2147$ |           | $y=-2E-08x^3+6E-05x^2-0.0562x+23.622$ | $y=1E-08x^3-7E-05x^2+0.1272x-65.432$ |
| $r=0.1543$                          |           | $r=0.8039$          | $r=0.4517$ |
| Relationship with MAP               |           |                     |           |
| $y=-1.7476x+26.013$                 |           | $y=-0.0788x^3+3.7071x^2-55.95x+282.2$ | $y=-1.3729x+44.318$ |
| $r=-0.7357$                         |           |                     |           |
| Relationship with MAT               |           |                     |           |
| $y=1E-07x^2-0.0003x^2+0.1662x+1.3595$ |           | $y=-0.0001x^3+0.0282x^2-1.7084x+40.58$ | $y=9E-05x^3-0.0237x^2+2.0334x-43.494$ |
| $r=0.7934$                          |           | $r=-0.7724$         | $r=0.4471$ |
| Relationship with P/T               |           |                     |           |
| $y=-0.0097x+47.525$                 |           | $y=-1E-09x^3+2E-05x^2-0.1175x+203.48$ | $y=-0.0044x+49.828$ |
| $r=-0.7467$                         |           |                     |           |

Note: $P < 0.05$, $P < 0.01$, $n = 752$. The same below.

Table 4. Relationship between SOC content and hydrothermal conditions in different MAP areas.

| MAP areas                           | <400 mm | 400 mm ~ 800 mm | >800 mm |
|-------------------------------------|---------|-----------------|---------|
| Some areas of Heilongjiang Province, Jilin Province, Hebei Province | 23      | 410             | 319 (307) |
| Number of samples                   |         |                 |         |
| $y=9E-05x^2-0.0951x^2+33.089x-3794$ |         | $y=2E-07x^3-0.0004x^2+0.2598x-38.663$ | $y=-8E-06x^2+0.0253x-4.2907$ |
| $r=0.6922$                          |         |                 |         |
| Relationship with MAP               |         |                 |         |
| $y=0.7515x^2-11.46x+51.479$         |         | $y=0.0098x^2-0.1097x^2-1.6591x+26.948$ | $y=-0.0219x^2+1.0418x^2-15.358x+81.85$ |
| $r=0.8908$                          |         | $r=0.8576$      |         |
| Relationship with MAT               |         |                 |         |
| $y=-8E-05x^3+0.0224x^2-1.6919x+47.837$ |         | $y=-3E-07x^3+2E-05x^2+0.0967x+4.7815$ | $y=0.1234x+4.5269$ |
| $r=-0.9031$                         |         | $r=-0.8233$     |         |
| Relationship with P/T               |         |                 |         |
| $y=2E-05x^2-0.1422x+265.05$         |         | $y=6E-10x^2-2E-06x^2-0.0183x+74.065$ | $y=5E-10x^2+1E-05x^2-0.0549x+113.39$ |
| $r=0.8808$                          |         | $r=0.8731$      |         |

Note: The data in ( ) in table 4 were the statistical results after deleting the data of the above 12 regions.

3.3. SOC content prediction model

Table 5 indicated that the first two factors with an eigenvalue greater than one were $\geq 10$ °C accumulated temperature and MAP. The $\geq 10$ °C accumulated temperature explained 65.03% of total variation and the MAP explained 33.52%. The cumulative contribution rate of the two reached 98.55%. Therefore, $\geq 10$ °C
accumulated temperature and MAP were finally taken as the principal components of the prediction model. After program operation, the model was presented as follows:

(1) Initial expression:

\[ C = \alpha + \beta \cdot \log(T) + \gamma \cdot \frac{C}{\log(P)} + \varepsilon \cdot \frac{C \cdot \log(P)}{\log(T)} \]

(2) Transformation:

\[ C = \frac{\alpha + \beta \cdot \log(T)}{\log(P) \cdot \log(T) - \gamma \cdot \log(T) - \varepsilon \cdot \log(P) \cdot \log(T)} \]

(3) Order:

\[ k_1 = \alpha + \beta \cdot \log(T) \]
\[ k_2 = \frac{\log(P) \cdot \log(T) - \gamma \cdot \log(T) - \varepsilon \cdot \log(P) \cdot \log(T)}{\log(P) \cdot \log(T)} \]
\[ k_3 = \frac{\gamma \cdot \log(T) + \varepsilon \cdot \log(P) \cdot \log(T)}{\log(P) \cdot \log(T)} = \frac{\gamma}{\log(P)} + \frac{\varepsilon \cdot \log(P)}{\log(T)} \]

(4) Then:

\[ C = \frac{k_1}{k_2} = +\beta \cdot \log(T) + k_3 \cdot C \]

(5) Order:

\[ k=C \]

(6) Then:

\[ k = C = \frac{\alpha \cdot \log(P) \cdot \log(T) + \beta \cdot \log(P) \cdot \log(T)^2}{\log(P) \cdot \log(T) - \gamma \cdot \log(T) - \varepsilon \cdot \log(P)^2} \]

In this model, \( C \) was the SOC content (g kg\(^{-1}\)), \( \alpha, \beta, \gamma \), and \( \varepsilon \) were constants, \( T \) was \( \geq 10^\circ \text{C} \) accumulated temperature (\( ^{\circ}\text{C} \)), \( P \) was the MAP (mm). \( k \) was defined as the humification constant of multi-year regional SOC, which was a constant under the comprehensive influence of hydrothermal conditions. The calculation results of the model were shown in table 6 and the final results of the model was as follows:

\[ k = C = -5.9779 \cdot \log(P) \cdot \log(T) + 1.6684 \cdot \log(P) \cdot \log(T)^2 \]
\[ \log(P) \cdot \log(T) - 1.3383 \cdot \log(T) - 0.6627 \cdot \log(P)^2 \]

The model validation was shown in figure 4. The ME, MAE and RMSE were 0.68, 2.13, and 2.79, respectively. The correlation coefficient \( (r) \) was 0.7454 \( (P < 0.01) \), reaching a very significant correlation. It showed that the value of SOC predicted by the model could basically reflect the real value of SOC in this area.
4. Discussion

On the micro scale, the spatial heterogeneity of SOC content was the result of the comprehensive action of natural and human factors, mainly including soil type, soil texture, terrain, land use mode, fertilization status, straw returning to the field and other factors (Gelaw et al. 2014, Schillaci et al. 2017, Tziachris et al. 2019). But on the macro scale, the change of SOC content was often caused by natural factors. Climate change had a great impact on the accumulation of carbon and nitrogen in larger regions (Chen et al. 2016, Wiesmeier et al. 2019). In agroecosystem, climate factors affected the change of SOC content through temperature and precipitation (Zhang et al. 2019). Temperature was the key factor affecting SOC decomposition, and soil moisture might be an important factor affecting SOC decomposition and its temperature sensitivity (Chen et al. 2020). The interaction of temperature and water significantly affected soil carbon sequestration (Xia et al. 2018, Piao et al. 2020).

The influence of temperature on SOC content was complex. On the one hand, temperature directly affected the accumulation of SOC through microbial activity. At the same fertility level, the higher the temperature, the higher the crop biomass, the more litter and crop stubbles returned to the soil, and the SOC content would be more likely to increase (Roper et al. 2021, Jat et al. 2019). On the other hand, SOC decomposition was sensitive to the increase of temperature. With the increase of temperature, the decomposition rate of SOC would accelerate, and the content would decrease (Lal 2018, Xu et al. 2019). Therefore, there might be some offsetting effect in this process. Precipitation could have a significant impact on the function and structure of agroecosystems, because water was the basic driving force of almost all chemical and biological processes, including crop survival and growth, photosynthesis, microbial activity and soil respiration, resulting in the accumulation and decomposition of SOC (Han et al. 2018b, Carter 2020). Although precipitation could significantly change soil respiration, it produced different effects under different circumstances. In the rainy season in humid areas, the increase of precipitation might significantly inhibit soil respiration and crop growth. In the dry season in arid or semi-arid areas, the increase of precipitation might play a promoting role (Yue et al. 2018, Han et al. 2018a).

The effects of temperature and precipitation on soil temperature and humidity were not independent, but interactive (Guanlin et al. 2017). With the increase of soil temperature, the activity of microorganisms and the content of derived compounds increased, which easily led to the degradation of unstable component SOC. However, the completion of this process also required the increase of precipitation (Wang et al. 2021). There was a significant positive correlation between SOC content and P/T in this study (figure 5). Similarly, some scholars

| Coefficients | Value | Standard error | t-Stat | P-value | Lower limit 95% | Upper limit 95% |
|--------------|-------|----------------|--------|---------|-----------------|-----------------|
| α            | -5.9779 | 0.1476          | -40.4898 | 0.0000 | -6.2680         | -5.6879         |
| β            | 1.6684  | 0.0388          | 42.9744 | 0.0000 | 1.5921          | 1.7447          |
| γ            | 1.3383  | 0.0097          | 138.5876| 0.0000 | 1.3193          | 1.3573          |
| ε            | 0.6627  | 0.0038          | 175.7015| 0.0000 | 0.6553          | 0.6701          |

Figure 4. Predicted value and real value of the SOC model.

Table 6. Results of SOC content model based on hydrothermal conditions.
also found that the change of hydrothermal gradient had a significant positive effect on the content of soil light fraction organic carbon (Liu et al 2021).

With different land uses, the SOC content and its response to climate change were different (Jia et al 2021). Zhang et al (2022) found that the SOC content of farmland in each geographical area of China was lower than that of grassland and forest land. Although temperature and precipitation would also affect the formation and evolution of SOC in forest land, grassland and wetland, SOC in farmland had certain uniqueness (Wu et al 2022). Farmland ecosystem carbon pool was the most active part of the global carbon pool. On the one hand, many studies confirmed that the active components of SOC, such as easily oxidized organic carbon, microbial biomass carbon, dissolved organic carbon and particulate organic carbon, in farmland ecosystem were higher than those in forest and grassland ecosystem, while the stable components of SOC, such as mineral-bonded organic carbon, heavy fraction organic carbon and inert organic carbon, were significantly lower than those in forest and grassland ecosystem, indicating that farmland ecosystem was weak in protecting SOC (Ramesh et al 2019, Li et al 2021). On the other hand, under the conditions of crop rotation and agricultural management with high fertilization intensity, the nitrogen accumulation of farmland soil was higher than that of other soil ecosystems (Conley et al 2009, Rong et al 2016), and farmland soil, especially topsoil, was vulnerable to strong human interference. The impact of climate factor on SOC decreased with the increase of soil depth (Albaladejo et al 2013, Li et al 2021). Therefore, farmland SOC had a direct feedback effect on climate change and had higher sensitivity (Zhang et al 2018, Ren et al 2020).

The SOC prediction model based on hydrothermal conditions has some limitations in this study. After all, climate is not the only natural factor affecting SOC content. After removing the influence of ‘abnormal’ high precipitation caused by topographic factors, the correlation between SOC content and MAP became better. It can be seen that topography is also an important factor in soil formation. It not only controlled the redistribution of hydrothermal conditions, but also affected the soil properties, material and energy flow in the ecosystem (Guo et al 2019, Hindersah et al 2021). In the future, the terrain, physical and chemical properties of soil and human factors (such as farming methods and fertilization) still need to be comprehensively considered to modify the model in the study, so as to improve its universality and popularization.

5. Conclusion

In this study, the spatial distribution characteristics of SOC content in eastern China were analyzed. Based on the influence of hydrothermal conditions on SOC content, the MAP, MAT, P/T, and \( \geq 10 ^\circ \text{C} \) accumulated temperature were selected for the research, and the prediction model of SOC content was established. The spatial heterogeneity of SOC content in eastern China was obvious. There were two break points in the relationship between SOC content and MAT, which were 10.42 \( ^\circ \text{C} \) and 20.75 \( ^\circ \text{C} \) respectively. The relationships between SOC content and hydrothermal conditions in different MAP areas were different. The effects of temperature and precipitation on SOC accumulation were also different. The same was true in the areas with different MAP. The effects of temperature and precipitation on SOC content were interactive rather than independent. P/T could be used as an important index to evaluate SOC content. It is effective and feasible to establish SOC content prediction model based on hydrothermal conditions, but other factors still need to be considered for correction.

Figure 5. Relationship between SOC content and P/T.
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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Author contributions

Conceptualization, Shutian Liu and Xiansheng Xie; methodology, Shutian Liu and Yanlin Hou; software, Xiansheng Xie; formal analysis, Xiaochuan Wang and Xianda Hou; data curation, Xinxin Feng and Keyu Lin; writing—original draft preparation, Shutian Liu and Shuojin Wang; writing—review and editing, Sen Dou and Mei Huang; and supervision, Yanlin Hou and Shugang Jia. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

Authors declare that they have no competing interests.

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