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Factors Acquisition and Content Estimation of Farmland Soil Organic Carbon Based upon Internet of Things

WU Qiulan[1], LIANG Yong[1], LI Ying[2], WANG Xizhi[3], YANG Lei[1], WANG Xiaotong[4]

(1. *School of Information Science and Engineering*, *Shandong Agricultural University*, *Tai'an* 271018, *China*; 2. *School of Economics and Management*, *Shandong Agricultural University*, *Tai'an* 271018, *China*; 3. *Institute of Agricultural Sciences of Yanzhou District in Jining*, *Yanzhou* 272100, *China* ; 4. *School of Geoscience and Surveying Engineering*, *China University of Mining and Technology*, *Beijing* 100083, *China*)

Abstract: Aiming at the shortage of sufficient continuous parameters for using models to estimate farmland soil organic carbon (SOC) content, an acquisition method of factors influencing farmland SOC and an estimation method of farmland SOC content with Internet of Things (IOT) are proposed in this paper. The IOT sensing device and transmission network were established in a wheat demonstration base in Yanzhou Distict of Jining City, Shandong Province, China to acquire data in real time. Using real-time data and statistics data, the dynamic changes of SOC content between October 2012 and June 2015 was simulated in the experimental area with SOC dynamic simulation model. In order to verify the estimation results, potassium dichromate external heating method was applied for measuring the SOC content. The results show that: 1) The estimated value matches the measured value in the lab very well. So the method is feasible in this paper. 2) There is a clear dynamic variation in the SOC content at 0.2 m soil depth in different growing periods of wheat. The content reached the highest level during the sowing period, and is lowest in the flowering period. 3) The SOC content at 0.2 m soil depth varies in accordance with the amount of returned straw. The larger the amount of returned straw is, the higher the SOC content.

Keywords: Internet of Things (IOT); soil organic carbon (SOC); factors acquisition; SOC content estimation; Soil-C model

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1 Introduction

In September 21, 2014, a joint report issued by Nature Climate Change and Nature Geoscience stated that according to the estimation of the Global Carbon Project, the CO_2 emissions in 2014 reached 4.4×10^9t, which is 2.5% higher than that in 2013 (Fuss *et al*., 2014). The increased CO_2 concentration in the atmosphere is the primary cause of global climate change (Reichstein *et al*., 2013; Robert *et al*., 2015). There are two main methods to reduce CO_2 concentrations: the first is reduction of carbon source, which means directly reducing greenhouse gas emissions, and the second is increase of carbon sink, which means absorption of greenhouse gases, especially CO_2 (Piao *et al*., 2011). According to the records, the organic carbon stored in continent soil is as high as 1500 Pg, which is about three times of that in the atmosphere (Lal *et al*., 1998, Lal, 2004; Chen, 2013; Xia *et al*., 2014). The continental ecological system (mainly including forest, grassland, farmland and wetland) has great potential for carbon sequestration. The global farmland carbon reserves account for over 10% of all continental carbon reserves (Zhang *et al*., 2014). Because of the short growing period, the farmland eco-

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Corresponding author: LIANG Yong. E-mail: liang_9322@126.com

logical system is greatly influenced by agricultural production management activities such as cultivation and fertilization, which lead to constant change in the quality and quantity of carbon stocks in farmland ecological systems. This becomes an important evidence of farmland ecological system's influence on the atmosphere carbon source/sink effect (Qin *et al*., 2016a). Based on modern technology, research into the carbon sink function of farmland ecological systems and the increase of farmland SOC content have an important influence on relieving climate change within a short period (Ghimire *et al*., 2012).

Methods to estimate SOC content include modelling methods, estimation based on soil or ecosystem type, relative relation statistics method and spectrometry methods. The model estimation method, which is widely used currently, mainly describes the soil carbon cycle process in a quantitative way with mathematics method, and simulates the dynamic changes of SOC content using computer, as well as estimating soil carbon storage situation and predicting future carbon sequestration potentials (Long *et al*., 2012; Yu *et al*., 2012; Jin, 2014). In recent years, considerable research has been conducted into SOC content estimation models such as Century model (Parton and Rasmussen, 1994; Bortolon *et al*., 2011; Xu *et al*., 2011), Rothamsted Carbon (RothC) model (Francaviglia *et al*., 2012; Peltre *et al*., 2012 Farina *et al*., 2013), Denitrification-decomposition (DNDC) model (Abdalla *et al*., 2011; Li R *et al*., 2014; Li *et al*., 2016; Liao *et al*., 2016), Soil-C model (Huang *et al*., 2001; Liu *et al*., 2001; Huang *et al*., 2008), *etc*. These models have been applied in a range of countries and regions. However, to date, there is no model that is suitable for all space and time dimensions. Each model has its uncertainties in estimation or prediction (Liu *et al*., 2015). The estimation results of SOC content vary greatly, because the researchers applied different research methods, data sources, techniques and parameters. Therefore, the existing models need to be improved in specific regions (Qin *et al*., 2016b; Zhang *et al*., 2016). As farmland SOC can be influenced by many factors such as soil characteristics, climate, cultivation system and management methods (Jin *et al*., 2000; Liu and Liu, 2014; Han *et al*., 2016; Hoyle *et al*., 2016), *etc*., the estimation of SOC content using models requires a large amount of continuous data. Continuous acquisition of factors influencing SOC is the key to increasing the precision of SOC estimation. Therefore, advanced technologies must be applied to increase precision and correspondingly reduce uncertainty of simulated results (Jiang *et al*., 2007).

To our knowledge, at present, there is little research into the real-time measurement of factors influencing SOC. The factors required for the estimation of SOC content based on models are generated through reorganization and analysis of data from general soil survey, former investigation materials and farmland experimental data, or through spatial interpolation of data from monitoring sites (Qin and Huang, 2010; Hou *et al*., 2011; Chai *et al*., 2015; Klumpp *et al*., 2016). As a result, relevant data are inadequate, poorly timing and discontinuous. Therefore, it is difficult to comprehensively simulate the spatial variation of real variables, which leads to inaccurate estimation results. The development of Internet of Things (IOT) technology has provided a safeguard for continuous acquisition of factors influencing SOC (Ma *et al*., 2014). Taking the wheat demonstration base in Yanzhou Distict of Jining City, Shandong Province, China, as the experimental area, this paper studies the methods of farmland SOC factors acquisition and content estimation based upon IOT and Soil-C model. Further study is made on the dynamic change of SOC content in different periods of wheat growth, which can propel the implementation of cultivation measures increasing farmland carbon sink.

2 Materials and Methods

2.1 Experimental area

Yanzhou District in Jining City is located in the southwest plain of Shandong Province, China, between 35°24′N–35°43′ N and 116°35′E–116°53′ E (Fig. 1).

According to the statistics of Institute of Agricultural Sciences of Yanzhou District in Jining, the total area is 651 km^2, with 40 000 ha of farmland, 75% of which is growing wheat and maize. This district lies in the semi-humid and warm temperate climate zone, featuring continental monsoon climate. According to the statistics of Weather Station in Yanzhou District, the annual average temperature is 13.6℃, with 733 mm of average annual rainfall, 2406–2903 hours of total annual sunlight and 1.247×10^6 kcal/m^2 of total annual solar radiation.

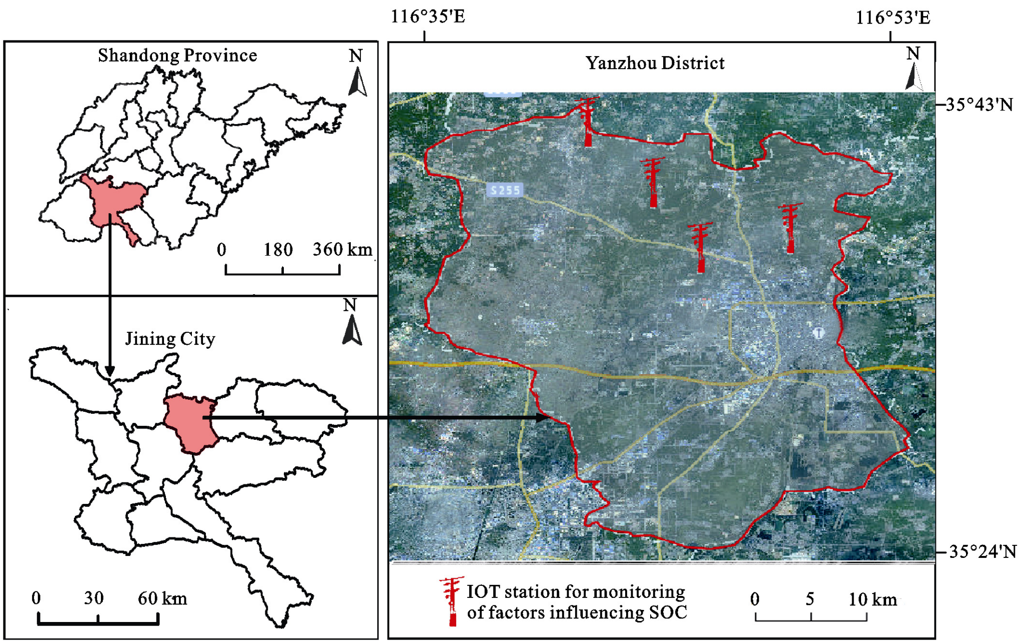

Fig. 1 Location of experimental area and distribution of Internet of Things (IOT) stations for monitoring of factors influencing soil organic carbon (SOC) in Yanzhou District, Jining City, Shandong Province, China

In the experimental area in Yanzhou, the main soil is typical meadow cinnamon soil, which accounts for 59.37%, and lime concretion black soil accounts for 33.01%. Fluvo-aquic soil accounts for 7.62%. The soil texture is mostly medium loam and the cultivation mode is the crop rotation system of winter wheat and corn. The soil is ploughed in early October after the maize harvest every year. The ploughed layer is about 0.2 m deep. The following year in mid-June, maize is sown without tillage after the wheat harvest. The straws of wheat and maize are smashed by machines and returned to the farmland. Maize straws are mixed into the soil through ploughing, while wheat straws are smashed and covered on the soil. Chemical fertilizer is mainly used (Ren *et al*., 2012).

According to the statistics of the Soil and Fertilizer Station in Yanzhou in October 2012, physical and chemical properties of the soil at 0.2 m depth are shown in Table 1.

Table 1 Soil physical and chemical properties at 0.2 m soil depth of study area in October 2012

Index	Value
Volume weight (kg/m^3)	1390
Total pore percentage (%)	59
Clay content (g/kg)	145
pH value	7.0
Soil organic carbon (g/kg)	10.14
Available nitrogen (mg/kg)	99.7
Rapidly available phosphorus (mg/kg)	23.9
Rapidly available potassium (mg/kg)	90.7

2.2 Analysis of farmland SOC content estimation model

Because of the diversity of farmland soil and the great differences in land management and operation modes with other countries, foreign models do not suit for the agriculture in China. Therefore, the Soil-C model, which was established by Huang *et al*., (2001) and based upon domestic experimental data, was chosen to simulate the dynamic change of SOC content. Some of the parameters of this model can easily be acquired through IOT technology.

The Soil-C model is (Huang *et al*., 2001):

$$\mathrm{d}C_i / \mathrm{d}t = K_i \times C_i \times f_\mathrm{T} \times f_\mathrm{W} \times f_\mathrm{S} \times f_\mathrm{pH}$$

$$\text{(for } C_i,\ i = 1, 2, s, \text{ for } K_i,\ i = 1, 2, 3) \qquad (1)$$

where the time step of the model is days (d); K_i is the first order kinetics rate constant. In the original model, the value of K_i is 0.025; 0.080×10^{-3}; 0.065×10^{-3} respectively; Here, C_i is the amount of organic carbon fractions (type i) at the time t. (i =1, 2, s) represent the easily decomposed components and difficultly decomposed components of external organic carbon and the original SOC. Assuming the initial amount of external organic materials is C_0, and decomposition rate is F, then the initial quantity of easily decomposed components (C_{10}) and difficultly decomposed components (C_{20}) are:

$$C_{10} = F \times C_0 \tag{2}$$

$$C_{20} = (1 - F) \times C_0 \tag{3}$$

The rate F is determined by initial N content (N, g/kg) and lignin content (L, g/kg):

$$F = \frac{(150 + 1.5N - 0.57L)}{100} \tag{4}$$

In Equ. (1), f_T, f_W, f_S, f_{pH} are the influence functions of soil temperature, moisture, texture and pH value to SOC decomposition respectively. Each may be estimated as follows:

$$f_T = Q_{10}^{\frac{T_s - 10}{10}} \tag{5}$$

where Q_{10} is the temperature index of organic carbon mineralization, which is taken as a constant 2.5, and T_s is the soil daily mean temperature (℃).

$$f_w = 0.49 \times \exp(3.88 \times W - 5.4 \times W^2) \tag{6}$$

where W is the soil water content (g/kg). In flooded conditions, f_W is taken as 0.65.

$$f_S = 1 - 0.26Clay \tag{7}$$

where $Clay$ indicates the content of clay with diameter < 0.005 mm.

$$f_{pH} = \frac{1}{1 + e^{-2.5(pH-5)}} \tag{8}$$

2.3 Acquisition system of factors influencing SOC based upon IOT

According to the Soil-C model, the factors influencing SOC which can be acquired continuously through IOT technology are soil temperature, soil moisture and soil pH value. In order to acquire continuous model parameters, an IOT sensing device was established in the experimental area to realize seamless sensing of factors influencing SOC and provide Soil-C model with real-time and precise information, according to the geographical features and soil types of the experimental area. Four monitoring stations were established in the experimental area (Fig. 1), as described in Table 2.

Photographs of the four IOT stations for the monitoring of factors influencing SOC are shown in Fig. 2.

Each monitoring station was equipped with sets of sensors. The parameters like soil temperature, soil moisture, pH value and spatial location could be provided. The SOC factor sensors were laid at 0.2 m depth. The acquisition system of factors influencing SOC consists of a sensing layer, transmission layer and a processing layer (Zhang Zenglin *et al.*, 2011; Jia *et al.*, 2014). The architecture of the acquisition system is shown in Fig. 3.

The sensing layer acquires factors influencing SOC quickly and precisely, providing basic data for SOC content estimation. The information from the sensing

Table 2 Coordinates of monitoring stations in experimental area

Monitoring station	Northern latitude	East longitude
Station 1	35°36′56″	116°49′05″
Station 2	35°36′03″	116°45′43″
Station 3	35°41′44″	116°41′36″
Station 4	35°39′00″	116°43′58″

Fig. 2 Four IOT stations for monitoring of factors influencing SOC in experimental area

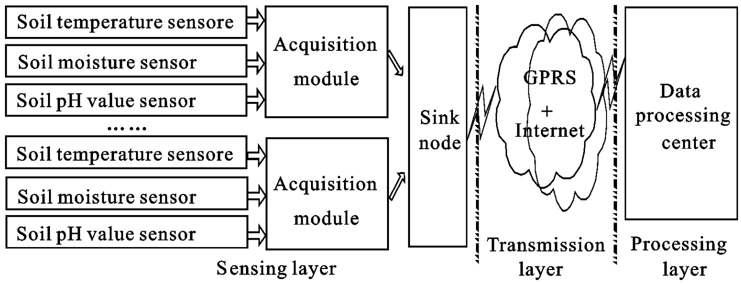

Fig. 3 Architecture of acquisition system. GPRS is General Packet Radio Service

layer provides factors influencing farmland SOC such as soil temperature, moisture and pH. According to the functional features of sensing layer, the architecture of the sensing layer is shown in Fig. 4.

The sensing layer is structured into modules. The information-sensing motherboard connects with functional and auxiliary modules through standard interfaces. Taking outdoor work into consideration, information sensing motherboard uses a microcontroller (MSP430F149) with low power dissipation. The transmission module is wireless (CC1100), which is highly cost-effective. The function module interface is mainly used for connecting with sensors laid out in the farmland soils. Soil moisture and temperature monitoring uses soil moisture and temperature sensor (SMS-II-485). The response time of this sensor is less than 1 s with working temperature of 40℃–80℃ and 5–24 V working voltage. Moisture precision is ±2% and the measurement scale is 0–100%. Temperature precision is ±3% and the measurement scale is 30℃–70℃. The soil pH sensor measurement scale is 0–14 with a precision of ±0.02 and the response time is less than 10 s. The sensing layer also has an auxiliary module, which includes a global positioning system (GPS) module and electronics supply module. The GPS module provides the sensing layer with GPS locating function. The electronics supply module is able to use either batteries or solar power to provide electricity.

The sensing layer acquires data such as soil temperature, moisture, pH value and spatial locations. The sensor node communicates through ZigBee, and transmits to a sink node, which is connected with the General Packet Radio Service (GPRS) module in the sensing layer by a serial port (Ma *et al*., 2014). Data flow from sensors to sink node, and are then sent to remote processing center through the GPRS module. Meanwhile, orders from the remote processing center are transmitted to the sink node through the GPRS module and serial port, which completes the information interaction between the remote processing center and sink node (Zhang, 2013; Gutierrez *et al*., 2014). The main function of the processing layer is the receiving, storage and processing of factors influencing SOC (Lin *et al*., 2015).

3 Results

3.1 Experimental data acquisition and analysis

(1) SOC content acquisition

In order to test the precision of the estimated value of SOC content using the IOT data and the model, a traditional method was used for test and analysis of real SOC content in the experimental area. This paper mainly studies the SOC content at 0.2 m soil depth within the cultivation layer. Soil samples were acquired from October 2012 to June 2015 in five key periods of wheat

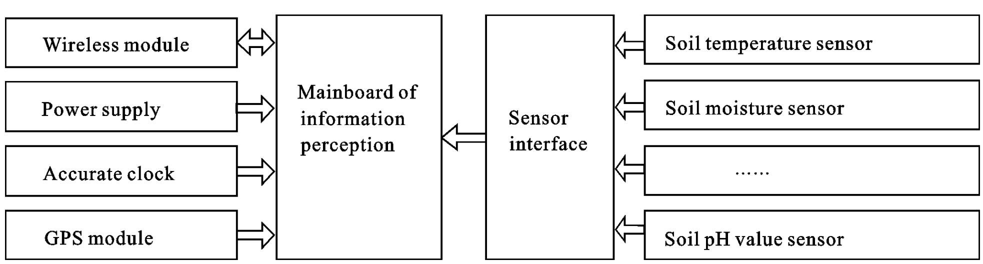

Fig. 4 Architecture of sensing layer

growth (sowing period in October 10, greening period in February 20, shooting period in March 15, flowering period in May 10, and harvesting period in June 10). Sample units were divided according to soil texture and fertility grade. Each sample unit was about 1000 m × 1000 m. In each unit, a mixed soil sample was acquired by mixing the samples from five different points at 0.2 m soil depth. The weight of a mixed sample was about 1 kg. Two hundreds soil samples were acquired in each key period. So 1000 soil samples were acquired in five key periods of wheat growth. The samples were dried naturally in the shade, smashed by wooden sticks, ground within a grinding bowl, and sifted by 100 mesh nylon sieves. Stones and botanical residual bodies were separated from the soil samples. The potassium dichromate external heating method was applied to measure SOC content (Wang, 2013; Li Xican *et al*., 2014). The results are shown in Table 3.

(2) Farmland SOC factors acquisition and analysis

From October 2012 to June 2015, the IOT devices were applied to observe continuously the factors influencing SOC in wheat farmland in the experimental area. Data were received every 10 minutes. The soil pH value monitored by IOT varied between 6.8 and 7.2 with an average value of 7 and little variability. The arithmetic means of soil temperature, soil moisture and pH value were calculated according to monitoring data because we specified a daily time step for the model. The results between October 2012 and June 2015 are shown in Fig. 5–Fig. 7.

Table 3 SOC content at 0.2 m soil depth using potassium dichromate external heating method from October 2012 to June 2015(Unit: g/kg)

	Sowing period	Greening period	Shooting period	Flowering period	Harvest period
2012–2013	10.16	9.83	8.85	7.65	9.96
2013–2014	10.39	9.46	8.86	7.97	10.29
2014–2015	11.91	11.16	10.75	9.38	10.45

The parameters including soil clay content, the external organic carbon and the initial quantity of difficultly decomposed components were taken from the observational and statistical data of the Soil and Fertilizer Station in Yanzhou. According to these data, the external organic carbon before the sowing of wheat mainly originated from returned maize straw. The maize

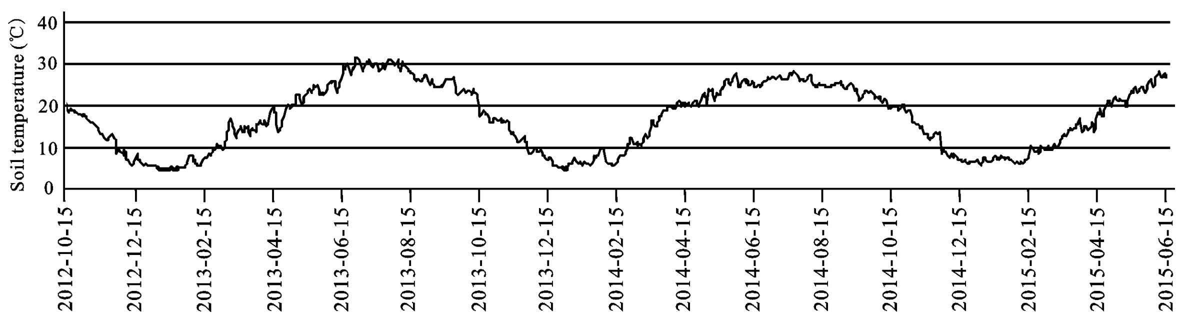

Fig. 5 Soil daily average temperature from October 2012 to June 2015 in experimental area

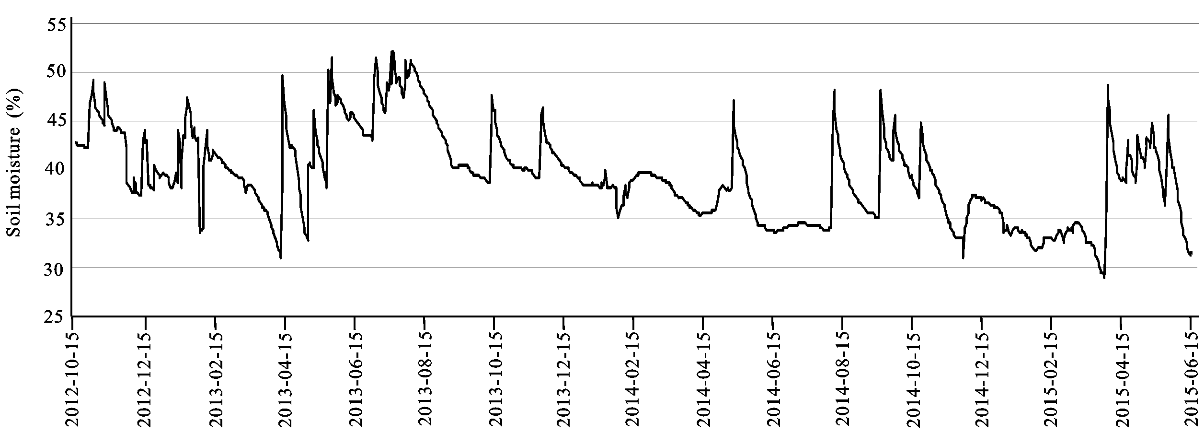

Fig. 6 Soil daily average moisture from October 2012 to June 2015 in experimental area

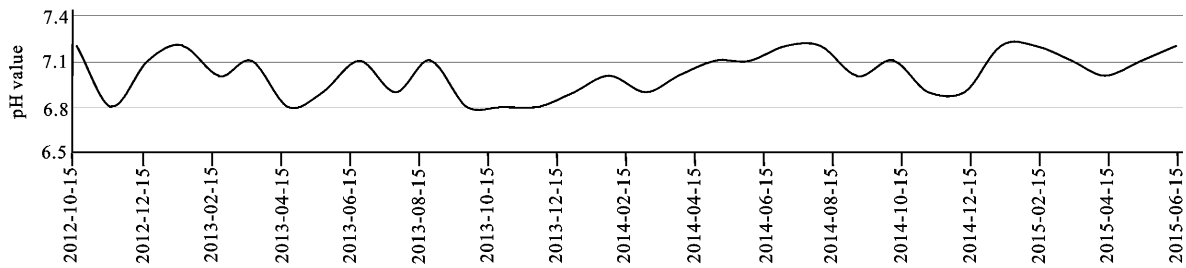

Fig. 7 Soil daily average pH value from October 2012 to June 2015 in experimental area

varieties grown in the experimental area were Zhengdan 958 and Nongda 108. Every year in early October, maize straws were smashed by machines and mixed into the farmland soil by ploughing. The total dry matter input averaged 9960 kg/ha in 2012, 10 820 kg/ha in 2013 and 12 500 kg/ha in 2014. The initial quantity of the difficultly decomposed component was 6475 kg/ha.

3.2 SOC content estimation with Soil-C model

The input parameters of the Soil-C model include soil temperature, soil moisture, soil pH value, soil clay content, the external organic carbon and the initial quantity of difficultly decomposed components. By providing these parameters to the Soil-C model, we generated the dynamic change curve of SOC in the experimental area in Yanzhou from October 2012 to June 2015 (Fig. 8). The solid line in Fig. 8 indicates the estimated results with the Soil-C model and the points in Fig. 8 indicate the laboratory test results of SOC content (Table 3).

In Table 3, the SOC content from laboratory tests may be considered the 'true' value. We can determine Δ_n as the true fault value: the difference between the estimated value and true value. Here, m is mean square error of the estimated value. We apply the formula of mean square error (Liang *et al*., 2009):

$$m = \pm\sqrt{\frac{[\Delta\Delta]}{n}} \tag{9}$$

where n is the monitoring frequency and $[\Delta\Delta] = \Delta_1^2 + \Delta_2^2 + ... + \Delta_n^2$. Generally, three times of the mean square error is taken as tolerable error. The mean square error of the estimated value corresponding to Table 3 was calculated through the mean square error formula and is presented in Table 4.

Table 4 indicates that the estimated SOC content approximately agrees with the measured value in the laboratory. It is feasible to acquire factors influencing farmland SOC based upon IOT technology and estimate SOC content with Soil-C model.

4 Discussion

As shown in Fig. 8, the SOC content has a clear dynamic change in different periods of wheat growth at 0.2 m soil depth. In the sowing period, as the maize straws have been returned to soil and have begun to decompose, the SOC content has the highest amount in the whole growing period. Later, between the sowing period and the greening period, the SOC content decreases

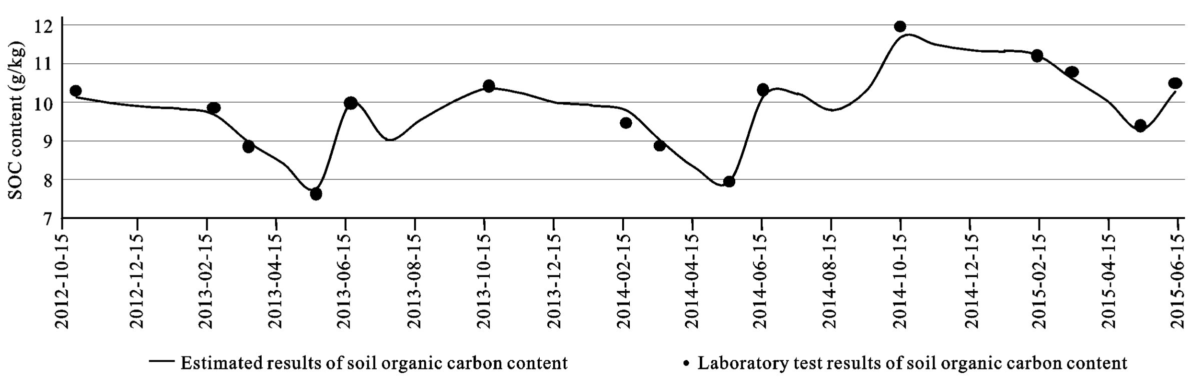

Fig. 8 Comparison diagram between estimated results and laboratory test results of SOC content

Table 4 Mean square error of estimated value

	Sowing period	Greening period	Shooting period	Flowering period	Harvest period
2012–2013	± 0.03	± 0.03	± 0.05	± 0.02	±0.02
2013–2014	± 0.02	± 0.09	± 0.03	± 0.01	± 0.02
2014–2015	± 0.07	± 0.03	± 0.03	± 0.02	±0.04

gradually as the temperature decreases and SOC decomposes slowly. Between the greening period and the flowering period, as temperature increases, and moisture is sufficient, the SOC decomposes faster and thus the SOC content decreases sharply. In the flowering period, the SOC content reaches the lowest amount during wheat growth. In the harvest period, the SOC content increases a little because of the perishing of wheat leaves and dying of wheat roots. After the harvest period, because of the returning of wheat straws, the SOC content tends to increase.

As shown in Fig. 8, the SOC content of farmland at 0.2 m soil depth varies in accordance with the amount of returned straws. The more the returned straws, the higher the SOC content at 0.2 m soil depth in the farmland soil.

It's very difficult to acquire a large amount of continuous data using traditional methods such as soil general survey and field experiment (Yu *et al*., 2006; Qin and Huang, 2010; Chai *et al*., 2015; Klumpp *et al*., 2016). A large amount of continuous factors influencing SOC content can be directly acquired using IOT technology (Fantacci *et al*., 2014). Therefore, uncertainty of simulated results is reduced.

The cycle of farmland SOC is a complex process affected by climate, organic material input and agricultural activities. Before the operation of the SOC dynamic model, initial values of difficultly decomposed components and easily decomposed components are required as the preliminary conditions for the model. Since there were differences among crop rotation systems, agricultural management styles and the input of external organic carbon many years before the simulation, the initial value of difficultly decomposed components might be different from real situations, which may affect the output results of the model. This may cause deviation between model outputs and the traditionally tested results.

The Soil-C model parameters were generated from measured results of various organic materials cultured in laboratory (Huang *et al*, 2001), which were mainly tested in Rice-wheat rotation fields (Liu *et al*, 2001; Yu *et al*, 2006). The soil property, cultivation system and management modes of the experimental area are different from those of the tested area to a certain extent, which may lead to certain deviation between model outputs and the traditionally tested results. Therefore, the model shall experience long-term modification based upon farmland ecosystem in the experimental area, in order to increase the precision of SOC content estimation in certain area.

5 Conclusions

This thesis studies factors influencing farmland SOC, establishes collecting system of farmland SOC factors based upon the IOT. The dynamic changes of farmland SOC content is simulated with SOC model using real-time data collected through IOT and statistics data. The development of IOT technology provides important means for real-time and continuous acquisition of factors influencing SOC. This provides a basic data safeguard for monitoring dynamic changes of farmland SOC content. The results show that it is feasible to acquire factors influencing farmland SOC based upon IOT technology and estimate SOC content with Soil-C model. Straw return has positive effect on the increase of SOC content. The research results can be used to guide the implementation of carbon sequestration measures of farmland, and the decision-making of relative policies for agricultural carbon sink compensation and mitigating the impacts from climate changes.

Because of the unevenness of soil physiochemical property, more monitoring points will lead to more representative data. However, large area layout of IOT sensing equipment requires high costs. Furthermore, the continuous data collected through IOT from discrete points in the region is not spatially continuous. Considering the shortage of IOT of collecting only 'point' data, future studies will aim at combining IOT and remote sensing technologies by structuring the fusion method of IOT real-time monitoring data based upon "point" and remote sensing spatial data based upon "area". The monitoring system fusing 'point' data and 'area' data will be established to realize point-to-area regional dynamic monitoring of SOC influencing factors and provide data support for large scale farmland SOC content estimation.

In addition, this experimental area is located on the plain, which is associated with minimal spatial variations of terrain, soil physiochemical property, climate and other factors. Therefore, further study is required to clarify whether this method is suitable for areas with complicated terrain and great spatial variations.

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