Evaluating the feasibility of GF-1 remote sensing comparison with hyperspectral data for soil organic carbon prediction and mapping

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Abstract. High-resolution remote sensing data play a very important role in agriculture. However, the major sources of high-resolution images are not owned by China. The Chinese “High Resolution Earth Observation Systems” was deployed in 2010, and several major projects have been implemented. The present study focused on assessing the feasibility of Gaofen (GF) multi-spectral data for monitoring bare soil organic carbon (SOC) at field and regional scales. The data sources are hyperspectra measured under laboratory conditions and simulated multi-spectral data from GF-1 remote sensing images. Partial least squares regression (PLSR) was used to estimate SOC. At the field scale, the SOC hyperspectral prediction model produced better \( R^2=0.9688 \), \( RMSE=0.3818 \), and \( RPD=5.6393 \) than the simulated multi-spectral SOC prediction model \( (R^2=0.8179, RMSE=0.9913, RPD=2.3401) \). At a regional scale, the SOC hyperspectral prediction model also produced a better \( R^2=0.9319 \), \( RMSE=1.097 \), and \( RPD=3.8758 \) than the simulated multi-spectral SOC predicted model \( (R^2=0.8445, RMSE=1.6574, RPD=2.4228) \). For the simulated GF-1 multi-spectra model, regional scale predications had advantages over field scale predictions. The spatial distribution characteristics of SOC measurements and predictions from hyperspectral data and simulated GF-1 multi-spectral data were similar. Thus, satisfactory performance of the predictive and calibrated models validates the feasibility of these methods for rapid large-scale SOC monitoring.

1. Introduction
Soil organic carbon (SOC) plays a major role in evaluating the effects of land use on soil quality indicators, which is increasingly being recognized as important for natural and agricultural ecosystems, both nationally and internationally [1-3]. SOC stock constitutes the largest pool of terrestrial organic carbon, acting as an important long-term sink for atmospheric carbon released by human activities [4-5]. SOC evaluation is important for a proper assessment of greenhouse gas emission effects under different climate-change scenarios. It is also of great importance for adjusting cultivated land fertility, and precise agriculture requires monitoring of SOC and its spatial distribution characteristics [6-8]. In recent years, visible near-infrared (vis-NIR) remote sensing has been developed as a useful tool for rapid and inexpensive soil organic matter monitoring [1, 9-10]. SOC monitoring by vis-NIR remote sensing and proximal sensory techniques is fast, simple and non-destructive and has recently attracted...
more interest. For example, the response range for SOC hyperspectral reflectance is mainly within the vis-NIR region, and there are negative correlations between SOC and hyperspectral reflectance [1, 10-12]. Many researchers have analyzed hyperspectral reflectance by derivative, logarithmic, differential, and other methods. Subsequent examinations of characteristic bands showed that correlation, multiple statistical regression, principal component analysis (PCA), partial least squares regression (PLSR) and neural networks (NN) were better for estimating SOC with vis-NIR hyperspectral remote sensing [3, 10, 12-15].

Laboratory testing methods are time-consuming, labor-intensive and inefficient; whereas, remote sensing technology has advantageously short data acquisition times, rich image information and low production costs. It has attracted much attention for dynamic spatiotemporal monitoring of soil properties over large areas. For example, Blasch et al. showed similar mapping results between field scale laboratory measurements of SOC and predictions made by RapidEye [16]. Zhang et al. established a regression model for surface soil SOC using the 3-band and 5-band from TM images, mapping the SOC in Fuxin town, Liaoning province [17]. Loiseau et al. and Peng et al. used Landsat 8 OLI images data to monitor and map clay and soil salinity content and at a large scale [18-19]. These studies indicate the high potential of using remote sensing to predict soil properties. However, the high time requirements and low resolution of remote sensing images make it difficult for them to meet research needs. The GaoFen-1 (GF-1) satellite, which was successfully launched at Chinese Satellite Launch Center April 26, 2013, offers a breakthrough combination of high spatial resolution, multispectral collection and high temporal resolution. It represents a reliable resource for large-scale agricultural remote sensing [20-22]. In this study, we assessed the potential of GF-1 data to predict SOC by performing experiments at field and regional scales compared with hyperspectral data. Models were built to simulate predicted SOC with hyperspectral data, and SOC spatial variation mapping was carried out in the study area. By analyzing and comparing the models and maps, the feasibility of making SOC predictions based on multispectral data was assessed. This analysis provided theoretical support for monitoring SOC at a large scale with multispectral data.

2. Materials and Methods

2.1. Data collection and processing

2.1.1. Soil collection and processing. Sixty-four soil cores were collected on 8 November 2017 from bare soil. Forty-two locations were collected in a 100 m×100 m field on a 16 m grid, and the other 22 locations were collected at a regional scale (Figure 1). In order to match the resolution of remote sensing images, all of the sampling locations were placed in the middle of remote sensing pixels, as best as possible. Coordinates of the sample sites were recorded using a GPS (GARMIN) instrument. On each slope, five soil cores were sampled at a depth of 0–20 cm. All samples were dried in an oven at 105°C and then sieved to 2 mm. Soil fractions smaller than 2 mm were homogenized, sub-sampled and then powdered to less than 250 μm in preparation for analysis. SOC content was determined using the potassium bichromate volume-external heating method [23].

2.1.2. Spectral collection and pre-processing. Spectral reflectance was acquired for the 64 soil samples (sieved and dried) on an ASD Fieldspec 3 portable Spectrometer (Analytical Spectral Devices Inc., Boulder, CO, USA). Each sample’s reflectance was computed as the average of 30 measurements in a spectral range of 350–2500 nm. From 350 to 1000 nm, the spectral sampling interval was originally set to 1.4 nm for a spectral resolution of 3 nm. From 1000 to 2500 nm, the spectral sampling interval was 2 nm for a spectral resolution of 10 nm. However, the reflectance provided was pre-processed by the ASD software and was consequently oversampled to 1 nm in both spectral ranges, leading to a total of 2151 spectral bands. This number was then reduced to 1961 by removing spectral bands within the 350–440 nm and 2400–2500 nm ranges, which had low instrumental signal-to-noise ratios. In order to reduce the influence of laboratory optical environment field differences and sample
grinding and screening, all data were processed by Savitzky-Golay 7-point smoothing, differential transformation and multivariate scattering correction. In the end, Savitzky-Golay and first-order differential transformation were implemented.

Figure 1. Study area and sampling site locations

2.1.3. GF-1 multispectral data acquisition and processing. High-resolution remote sensing data play an important role in agricultural monitoring. The launch of the Chinese “High Resolution Earth Observation Systems” allows for superb high-resolution remotely sensed images (GF series) to be received with spatial resolution, scanning width and revisit periods that equal or even surpass those of similar foreign satellites. GF-1 carries two sensors: a wide field view sensor (WFV sensor) and a panchromatic multispectral sensor (PMS sensor). The WFV sensor can acquire multispectral images in blue, green, red and near-infrared bands with 16-m spatial resolution and 4-day temporal resolution. The PMS sensor can acquire panchromatic multispectral images (PAN) with 41-day temporal resolution. The detailed sensor parameters for GF-1 are described in Table 1.

| Sensor | Spatial resolution | Blue  | Green | Red   | NIR   | Swath (km) | Repeat cycle (d) |
|--------|--------------------|-------|-------|-------|-------|------------|------------------|
| WFV    | 16                 | 0.45-0.52 | 0.52-0.59 | 0.63-0.69 | 0.77-0.89 | 800         | 4                |
| PMSc   | 2 (PAN)/8          | 0.45-0.52 | 0.52-0.59 | 0.63-0.69 | 0.77-0.89 | 60          | 41               |

cWFV, wide field view.

bNIR, near-infrared.
cPMS, panchromatic multispectral sensors.

In this study, remote sensing data were acquired on 8 November 2017, coincident with the ground sampling (Figure 1). Multispectral images at 16-m resolution were acquired at 4 combined widths of more than 800 km in order to utilize the combined high resolution and wide-range imaging capabilities of the satellite. The data were corrected by FLAASH atmosphere to eliminate the radiation error caused by atmospheric scattering in the image. We took a RapidEye image as a reference for geometric correction, and controlled geolocation errors to within 0.5 pixel. The soil spectral curve was resampled in the vis-NIR range on the basis of the GF-1 WFV sensor response function (Figure 2). The algorithm is defined as follows:
Where, \( R_i \) is the reflectance of GF-1 sensor in i-band, \( \phi(\lambda) \) is the response function of i-band at wavelength at \( \lambda \), and \( r(\lambda) \) is the reflectance at wavelength at \( \lambda \).

\[
R_i = \frac{\sum_{i=1}^{n} r(\lambda) \phi(\lambda)}{\sum_{i=1}^{n} \phi(\lambda)}
\]

(1)

Figure 2. The reflectance response function of GF-1

The soil vegetation index is constructed using different wave bands, and it is often used to describe plant growth. Crop leaves strongly absorb in the red band and strongly reflect in the near-infrared band, which is the physical basis of vegetation remote sensing monitoring. Different vegetation indexes are obtained from different combinations of the values from these two bands. According to previous studies, improved predictions of the soil vegetation index are constructed using the ratio soil index (RSI) and normalized difference soil index (NDSI) [19, 24]. Therefore, the first and fourth GF-1 data bands were used to construct these soil indices. Modeling predictions using GF-1 simulated data were carried out and correlated with direct SOC measurements.

2.1.4 Model construction and accuracy estimation. PLSR is one of the most popular multivariate techniques for spectral calibration and prediction. It is closely related to principal component regression (PCR). Both methods reduce the number of variables in the prediction set. In PCR, the predictor variables are converted to principal components that are then ranked in order of the variance for which they account, regardless of their covariances with predictands. One simply decides how many to retain and then uses them as predictors in the subsequent regression. In PLSR, this arbitrary decision is largely avoided because the technique reduces the number of variables in the predictor set by selecting successive orthogonal factors from the variance-covariance matrix in a way that maximizes the covariance between the predictors and the response variable or variables (there may be more than one variable being predicted). There is a risk of over-fitting or under-fitting, and to avoid this, we used the leave-one-out cross-validation method to find the optimal number of calibration factors that minimize prediction error variance. For details, see Martens and Næs [25]. The determined coefficient (\( R^2 \)), root mean square error (RMSE), standard calibration error (SEC), observed value standard deviation (SD), relative error (RE) and standard prediction error ratio (RPD) were used to evaluate model calibration. Further, \( R^2 \), RMSE and RPD were used for accuracy estimation and model evaluation in this study.

(1) determined coefficient (\( R^2 \))

\[
R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]

(2)

where \( y_i \) is the measured values of sample, \( \hat{y}_i \) is the predicted values of samples, and \( \bar{y} \) is the average value of samples.
(2) root mean square error (RMSE)

$$\text{RMSE} = \left( \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \right)^{\frac{1}{2}}$$

$y_i$ is the measured values of sample, $\hat{y}_i$ is the predicted values of samples, and $n$ is the number of samples.

(3) standard prediction error (SEP)

$$\text{SEP} = \left( \frac{1}{n-1} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \right)^{\frac{1}{2}}$$

$y_i$ is the measured values of sample, $\hat{y}_i$ is the predicted values of samples, and $n$ is the number of samples.

(4) Ratio of standard deviation to SEP (RPD)

$$\text{RPD} = \frac{\text{SD}}{\text{SEP}}$$

SD is standard deviation of measured values.

2.2. Inverse distance weighting (IDW) for soil mapping

IDW interpolation explicitly works on the assumption that things which are closer to each other are more alike than those that are farther apart. In this case, the nearer SOC values have similar characteristics because their spatial dependence is based on “The First Law of Geography”. It is therefore proposed that IDW can be used to predict a SOC that is optimal over other interpolation methods, such as spline and kriging interpolation [26-27]. IDW can be expressed by the following equation:

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i)$$

$Z^*(x_0)$ is the value of $x_0$, $Z(x_i)$ is measured SOC value, $\lambda_i$ is weight assigned to each measured value, greater weight will be assigned to the points which are closest to the target location, and $\Sigma \lambda_i = 1$, $n$ is the number of known SOC for prediction.

3. Results

3.1. Characteristics of different SOC content groups

The 64 soil samples were divided into four different ranges of SOC (less than 10 g kg$^{-1}$, 10–15 g kg$^{-1}$, 15–20 g kg$^{-1}$ and greater than 20 g kg$^{-1}$), and the spectral curves of the groups are shown in Figure 3. The characteristics of SOC spectral curves for different groups were similar, and at higher SOC the absorption in Vis–NIR was stronger. The slope of the spectral curve was in trapezoidal decline at 400–600, 600–780 nm and 780–1350 nm. At 1400 nm, 1900 nm and 2200 nm, there were significant water absorption peaks.

3.2. Correlation analysis between soil measurements and spectral data

Correlation analysis between reflectance spectra or other transformed forms and SOC content showed that the first derivative spectrum could best convey subtle changes in the spectra. Analysis of the correlation between first derivative spectrum (400–2500 nm) and SOC (Figure 4) showed that higher correlation coefficients were in the visible range, particularly at 424, 445, 495 and 868 nm, and a maximum correlation magnitude of -0.56 was observed. In the NIR range, the peak correlation values were at 1402, 1420, 1913, 2039, 2162, 2261, 2336 and 2335 nm, with a maximum magnitude of -0.49.
Table 2 shows that the correlations between GF-1 simulated spectrum and SOC measured at the field scale and at the regional scale. The correlation of GF-1 simulated spectra with NDSI and RSI indices gradually decrease in the order of blue, green, red and near infrared. The RSI index was the most sensitive to SOC. At the field scale, the maximum correlation coefficient reached -0.558; and, at a regional scale, the maximum correlation coefficient was -0.535, which indicated that the soil index chosen can effectively improve the SOC predictions made by simulated data.

### Table 2. Correlation coefficients between simulated GF-1 multi-spectral data and SOC

| Scale     | Bands | Indices |
|-----------|-------|---------|
|           | Blue  | Green   | Red    | NIR   | RSI    | NDSI   |
| Field     | 0.515 | 0.430   | 0.383  | 0.306 | -0.558 | -0.456 |
| Regional  | 0.501 | 0.426   | 0.351  | 0.283 | -0.535 | -0.442 |

#### 3.3. Predicted SOC model

Predictions from simulated GF-1 multi-spectral data models built with the first differential of reflectance, Savitzky-Golay smoothing, and RSI are shown in Figure 5. The SOC model was built using all 22 regional scale samples and 42 field scale samples. According to the previous studies [28-30], models are good predictors when RPD is greater than 2, models can make coarse estimates when RPD is between 1.4 and 2, and models cannot be used for predictions when RPD is less than 1.4. On this basis, all of our predictive models provided good SOC predictions. The hyperspectral model (Figures 5a and 5b) performed better than the simulated GF-1 multi-spectral model (Figures 5c and 5d) on the basis of $R^2$, RMSE and RPD values obtained with these calibrated models. That is, at the field scale, the hyperspectral SOC prediction model (Figure 5a) produced better $R^2=0.9688$, RMSE=0.3818 and RPD=5.6393 than the simulated multi-spectral (Figure 5c) SOC prediction model ($R^2=0.8179$, RMSE=0.9913, RPD=2.3401). At a regional scale, the hyperspectral SOC prediction model (Figure 5b) also produced a better $R^2=0.9319$, RMSE=1.097 and RPD=3.8758 than the simulated multi-spectral (Figure 5d) SOC prediction model ($R^2=0.8445$, RMSE=1.6574, RPD=2.4228). Focusing on the simulated GF-1 multi-spectral models, the SOC prediction model at the regional scale (Figure 5c) showed advantages over that at the field scale (Figure 5d). Thus, this model provides a feasible method for rapid SOC monitoring at a large scale.

#### 3.4. SOC maps

The IDW method was applied to map measured SOC values, ASD hyperspectral reflectance and RSI derived from simulated GF-1 multi-spectral prediction values. Figure 6 shows the maps at the field scale, and Figure 7 shows the maps at a regional scale. At the field scale, higher SOC content appears in the west and a lower SOC content appears in the east. The three maps generated from measured SOC, hyperspectral reflectance and RSI predicted values, display a similar spatial distribution. At a regional scale, SOC is shown with a higher content in the east and a lower content in the west, and comparisons of the three maps indicate that all of them provided good SOC estimates.
Figure 5. Predicted SOC by PLSR models based on ASD hyperspectra and simulated GF-1 multi-spectra (a) regional scale SOC predicted by ASD hyperspectra; (b) field scale SOC predicted by ASD hyperspectra; (c) regional scale SOC predicted by simulated GF-1 remote sensing images; (d) field scale SOC predicted by simulated GF-1 remote sensing images.

Figure 6. SOC field scale maps generated from 42 samples (a) measured SOC; (b) ASD hyperspectral reflectance; (c) RSI derived from simulated GF-1 multi-spectra.
Discussion

Remote sensing technology offers opportunities for estimating, mapping and monitoring various soil properties [16, 31-32]. The key advantage of remote sensing is rapid large-scale acquisition of soil surface information, though vegetative cover influences the accuracy. In this paper, models showed satisfactory SOC estimation, especially the simulated GF-1 multi-spectral model, which presented better predictions of measured SOC at a regional scale ($R^2=0.8445$, RMSE=1.6574, RPD=2.4228) than at the field scale ($R^2=0.8179$, RMSE=0.9913, RPD=2.3401). Given the small sample size, these results indicate good SOC estimations. For the calibrated model, the field scale (Figure 5c) prediction had $R^2=0.8635$, RMSE=0.9497 and RPD=2.3763; and the regional scale (Figure 5d) prediction had $R^2=0.7570$, RMSE=2.0949 and RPD=1.9567. This demonstrates that the regional scale model is less robust than the field scale model. In the future, we need to obtain more samples to validate the predictions.

On the basis of $R^2$ and RPD judgements, the predictive accuracy of all models were relatively high which may reflect sample sizes. Generally, when sample sizes are small, $R^2$ values for a model will be higher, and vice versa. On the other hand, Leone et al. obtained $R^2$-values ranging from 0.84 to 0.93 and RPD values ranging from 2.36 to 2.53 from local soil predictive models based on 374 soil samples [33]; Sithole et al. obtained the most accurate model in predicting SOC ($R^2=0.993$, RMSE= 0.157, RPD=2.55) with 324 soil samples [34]. These imply that the models in our study can be used to estimate SOC. Though, in consideration of the GF-1 spatial resolution, sample locations were selected in the middle of pixels to reduce field scale error.

Maps generated at the field scale with measured and predicted SOC values showed heterogeneous spatial characteristics. This may be a result of microrelief and fertilizing. In the eastern part of the field, water flows from south to north in the South Water North Canal, which influenced the SOC, especially where the land was ploughed and organic fertilizer was added to bare soil. At a regional scale, the SOC spatial distribution indicated by various methods was homogeneous.

However, it should be noted that we only analyzed and compared GF-1 sensor data. If additional sensors could be analyzed in the future, it could improve applications of multispectral images to evaluate and map SOC at a large scale. Moreover, in order to predict and map SOC content more accurately, it will be necessary to improve and enrich the model with strategic sampling of different soil types and elevations.

Conclusions

All of the models provided good predictions of SOC content. The hyperspectral model performed better than the simulated GF-1 multispectral model. On the basis of observed $R^2$, RMSE, and RPD values, at a large scale, the simulated GF-1 model shows good potential for estimating SOC. Maps of predicted and measured SOC values demonstrate that the hyperspectral reflectance and simulated GF-1 models produced similar spatial distributions at both the field and regional scales. These results show that the great potential GF-1 remote sensing has to estimate soil properties of bare soils.
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