Geoderma 275 (2016) 55–66

Contents lists available at ScienceDirect

Geoderma

journal homepage: www.elsevier.com/locate/geoderma

UAS-based soil carbon mapping using VIS-NIR (480–1000 nm) multi-spectral imaging: Potential and limitations

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ARTICLE INFO

Article history:
Received 25 December 2015
Received in revised form 18 April 2016
Accepted 18 April 2016
Available online 3 May 2016

Keywords:
UAS
Multi-spectral
Soil organic carbon
Mapping
Soil spectra
Remote sensing

ABSTRACT

Traditional methods to assess the soil organic carbon (SOC) content based on soil sampling and analysis are time consuming and expensive, and the results are influenced by the sampling design. The aim of this study was to investigate the potential of UAS (Unmanned Aerial Systems) multi-spectral imagery (480–1000 nm) for estimating the SOC content in bare cultivated soils at a high spatial resolution (12 cm). We performed UAS analysis on the Hoosfield Spring Barley experiment at Rothamsted (UK) where adjacent plots with distinctly different SOC contents, due to different long-term management practices, provide a valuable resource to evaluate this approach. We acquired images (wavelength: 480–550–670–780–880–1000 nm) at an altitude of 120 m over an area of 2 ha using a multi-spectral camera mounted on an UAS. The high-resolution images captured small-scale variations at the soil surface (e.g. shadows, tillage and wheels marks). After a projection in new dimensions by a PCA, we calibrated a support vector machine regression using observations from conventional soil sampling and SOC measurements. The performance of the calibration had a R^2 of 0.98 and a RMSE of 0.17%C. A cross-validation showed that the model was robust, with an average R^2 of 0.95 and a RMSE of 0.21%. An external validation dataset was used to evaluate the predicted spatial patterns of SOC content and a good fit with an RMSE 0.26%C was obtained. Although this study shows that the methodology has a clear potential for use in precision agriculture or monitoring important soil properties following changes in management, we also identify and discuss its limitations and current shortcomings.

1. Introduction

Soil organic carbon (SOC) can be an important sink or source of atmospheric carbon dioxide (CO2) (Lal, 2004; West and Post, 2002; Amundson, 2001; Post and Kwon, 2000; Karhu et al., 2014). Consequently, it is an important component of any terrestrial C sequestration strategy (Powlson et al., 2012). Soil organic carbon is also a key factor controlling soil quality as it is closely related to the structural stability of soil aggregates, soil fertility and plant growth (McBratney et al., 2014). Past research has shown the effects of management practices on soil organic carbon dynamics and the tendency for SOC to move asymptotically towards a new equilibrium (Johnston et al., 2009) following changes in land use and management (e.g. additions of Farm Yard Manure (FYM)). However, it may take decades for soil SOC stocks to reach a new stable equilibrium. As a result, monitoring the impact of changes in land use, management and climate on soil C stocks is of interest to scientists, farmers and environmentalists. However, traditional methods to assess SOC storage based on soil sampling and analysis are time consuming and expensive (Govers et al., 2013; Cambou et al., 2016), and the resulting assessments are largely influenced by the sampling design (Vašát et al., 2010; Brus and Heuvelink, 2007; Minasny and McBratney, 2006).

In response to these challenges, a broad range of soil spectroscopic methods have been developed to measure simultaneously several soil properties (i.e. Vohland et al., 2014; Roberts et al., 2004). Under laboratory conditions, the estimation of SOC content by means of a spectrometer is now well established and the associated error has the same order of magnitude as those obtained by standard laboratory analytical methods (Aldana Jague et al., 2016; Nocita et al., 2015; Doetterl et al., 2013; Stevens et al., 2006; Sørensen and Dalsgaard, 2005). Portable spectrometers, which can also be used for in-situ monitoring of soils, are increasingly used but the error associated with the SOC estimations depend of the utilization conditions (e.g. RMSE of 0.9–1.5%C for a range of 0.5–8.9%C for Kühnel et al., 2014). Mouazen et al. (2007) used a fiber optic in a chisel which was pulled through the soil by a tractor in order to continuously measure soil spectra on the connected spectrometer. This allowed the SOC content to be estimated with an error of c. 0.48%

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http://dx.doi.org/10.1016/j.geoderma.2016.04.012
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(for a SOC content ranging from 0.7 to 6%C). Knadel et al. (2015) combined on the go spectroscopy with electrical conductivity and temperature sensors to map the SOC content and particle sizes. They obtained a relatively small prediction error (c. 0.14%C for a range of 1.37–3.34%C) by combining different sensors. Although these methods have large potential to monitor soil properties at very fine spatial scales, there are still some major limitations. These limitations arise mainly from (i) the fact that soil reflectance is strongly influenced by soil surface characteristics such as soil roughness and moisture increasing the error prediction (Croft et al., 2009, 2012; Morgan et al., 2009; Anderson and Kuhn, 2008), (ii) the limited spatial coverage of the measurement that can practically be done by on-the-go measurement and (iii) the laborious and costly nature of in-situ field sampling (Cambou et al., 2016).

Other studies have measured the soil reflectance at larger spatial scales (i.e. regional to national) for estimating topsoil SOC using airborne spectroscopy. For example, Stevens et al. (2006) used a CASI + SASI sensor (444–2500 nm) mounted on an aircraft to detect the carbon stock change at the regional scale but have reported difficulty in calibrating the spectral models due to various disturbing factors such as soil moisture and differences soil types. As a result, the discriminating power of the approach in terms of detecting SOC stock change was reported to be small (Stevens et al., 2006). Gomez et al. (2008) used data from the Hyperion satellite in order to estimate the SOC content, but the low resolution (30 × 30 m) and excessive noise did not allow accurate SOC results to be obtained. The variability in the signal caused by the diversity in soil type and soil moisture content, prevents a clear interpretation of the signal reflecting the variation in SOC content. Consequently, the method is not accurate enough to be of practical use in managing SOC in agricultural systems. Chen et al. (2000) used Red-Blue-Green (RGB) aerial photography to map the SOC content over 115 ha on a dry, bare soil and obtained a strong correlation between the SOC samples and RGB photography ($R^2 = 0.97$). However, they showed that variable Fe contents adversely affected prediction accuracy when only the RGB bands were used. Indeed, Fe oxides (Goethite and Hematite) strongly affect visible soil color with a peak absorption at 480, 529, and 650 nm (Viscarra Rossel and Behrens, 2010) and can affect all the RGB bands.

Recently, the costs of both Unmanned Aerial Systems (UAS) and multi-spectral cameras have fallen substantially whilst their specifications and performance have increased, opening up the possibility for their widespread use for vegetation and soil surface monitoring (Zhang and Kovacs, 2012). UAS carrying light sensors are already successfully used for monitoring vegetation (Baluja et al., 2012; Zarco-Tejada et al., 2009) and for precision agriculture (e.g. Primicerio et al., 2012). The main advantages of UAS-based sensing are (i) the cost-effective and flexible deployment capability, relative to large-scale satellite or airborne remote sensing methods and (ii) the capability to cover larger areas at a high spatial and temporal resolution, when compared to on-the-go sensor. However, to our knowledge a systematic investigation into the use of UAS-borne imagery for estimating the SOC content of agricultural soils is still lacking. Here, we aim to address this issue.

The specific objectives of this study were (i) to develop a procedure for acquiring high-resolution multi-spectral information from low-altitude imagery and (ii) to test whether low-altitude multi-band images can be used to accurately predict spatial patterns of SOC at a very high spatial resolution (12 cm). In order to evaluate its potential, we utilized one of the Rothamsted Long-term Experiments (LTEs) in the SE England (UK). Finally, we discuss the potential of UAS-based sensing for monitoring SOC changes on arable land subject to different manure and fertilizer management practices.

2. Materials and methods

2.1. Study area

Rothamsted is home to the oldest continuing agricultural field experiments in existence (Anon, 2006). Some of these LTEs contain adjacent plots with contrasting SOC contents. Consequently, they provide a valuable resource for systematically testing new remote sensing approaches for measuring SOC. This study focuses on the Hoosfield Spring Barley Experiment. The experiment was established in 1852 on a Stagnogleyic paleo-argillic brown earth, with a loamy surface layer overlying clay-with-flint (Warren and Johnston, 1967; Bull et al., 1998), to test the effects of mineral fertilizers (supplying N, P, K, Mg and sodium silicate) and organic manures (FYM, rape cake and castor meal) on the growth and yield of spring barley (Fig. 1). In 1852 FYM applications began on plots 71 and 72; they stopped in 1871 on plot 71, but still continue today on plot 72. In addition, annual FYM applications began on plot 73 in 2001 and still continue today. All the others plot received only inorganic fertilizer inputs (see Rothamsted research, 2006 for a full description of the treatment). These long-term FYM and inorganic fertilizer inputs have resulted in contrasting SOC contents (Glendining et al., 1997). Plots 72, 73 and 71 have SOC contents (%C) of up to 3.8%, 2% and 1.4% respectively. In contrast, most of the other plots have a SOC content of around 1%C.

2.2. Tetracam Mini-MCA6 camera

We used a Mini-MCA6 from Tetracam Inc. (Chatsworth, USA) to acquire multi-spectral images. The main advantage of this camera is that, despite the fact that it is small (13.4 × 9.3 × 7.8 cm) and light (1080 g including the battery), it detects six spectral bands. In addition, the sensitivity range of the camera is between 450 and 1050 nm (visible and near infrared), but the sensitivity of the sensor is not the same for all wavelengths (http://www.tetracam.com/Products-Mini_MCA.htm). The wavelengths for each channel are chosen using specific filters. In this work the following wavelengths were selected: 480–550–670–780–880–1000 nm (± 10 nm). These wavelengths were chosen so that they were equally distributed along the sensitivity range and ensured the capture of specific features, including the presence of iron oxides (peak absorption at 480, 529, 650 and 880 nm Viscarra Rossel and Behrens, 2010) and vegetation (channels 550, 670, 780 and 880 nm, Nichol and Lee, 2005). Each image was 1280 × 1024 pixels and the camera has a Field Of View (FOV) of 38.3 × 31.0 deg. This implies that at an altitude of 100 m the pixel size is 0.054 m and the image size is 69.4 × 55.4 m. We used a fixed exposure time of 2 ms to take the images. The camera has a master channel where the exposure is applied, the five others slave channels have different exposure times in order to correct for the sensor sensitivity. The configuration of these parameters was provided by Tetracam Inc.

2.3. UAS Octocopter Mikrokopter-XL

We mounted the Mini-MCA6 on a commercially available multirotor Unmanned Aerial System (UAS) platform, the Mikrokopter-XL. This is a light weight Vertical Take-Off and Landing system equipped with eight independent electrical motors. A predefined flight pattern (coordinate, altitude, velocity) can be uploaded to the UAS which can be flown by auto-pilot using the internal GPS. The Mikrokopter UAS has a size of 0.8 m by 0.8 m and can fly with a payload of up to 1.5 kg. We equipped the UAS with a gyro-stabilized gimbal where the camera Mini-MCA6 was fixed, to ensure the camera pointed towards the ground at all times during the flight. The flight duration depends on the total payload, the type of batteries, the flight altitude and the wind. With the payload described above a flight duration of 7–10 min was achieved.

2.4. Image acquisition

We acquired the multi-spectral images in April 2014 at the solar zenith (between 11 am–1 pm) and with a cloudless sky. Vegetation cover on the field was small; plant emergence occurred about a week before the flights and the plants were <1cm tall. The soil surface was dry,