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# Change detection of soils under small-scale laboratory conditions using imaging spectroscopy sensors

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ABSTRACT

Change detection techniques aim to identify changes between two or more images taken at different times. In this paper, we explore the capabilities of identifying changes in an unsupervised manner between different soil types using two laboratory HySpex imaging spectroscopy sensors in the visible near infrared (VNIR) and short-wave infrared (SWIR) spectral ranges. The experiment was carried under controlled laboratory conditions with the same lighting and no atmospheric distortions. The 69 selected soil samples covered the arid and semiarid climate zones of Israel. The well-known change vector analysis technique was used to generate the difference image, and several thresholding methods were tested to generate the final binary change map. The performance capabilities of the VNIR, SWIR and combined VNIR–SWIR sensors were examined. Our study demonstrates that changes in different soil types can be identified using imaging spectroscopy sensors; the SWIR sensor generated better change detection capabilities than the VNIR sensor, and the combination of the two sensors did not outperform the SWIR sensor alone. Results showed that it is important to combine a spectral domain thresholding approach with a spatial domain thresholding approach. The benefit of combining these approaches is a low false-alarm rate with a relatively high probability of detection. Although the change experiment was conducted under almost perfect conditions without any atmospheric or lighting differences, the change detection techniques did not detect all soil type changes and changes between spectrally similar soils remain undetected. The results of this study can be further extended to other spatial scales and can provide a foundation for soil change detection using upcoming imaging spectroscopy satellite platforms that acquire spatial–spectral–temporal information.

## 1. Introduction

Remote sensing of soil using hyperspectral remote sensing (HSR), also known as imaging spectroscopy (IS), is a growing field (Ben-Dor et al., 2009). The accumulated knowledge gained over the past 20 years in the soil spectroscopy discipline (Ben-Dor and Banin, 1995; Buddenbaum and Steffens, 2012; Nocita et al., 2013; Rossel and Behrens, 2010), and the recent development and availability of HSR sensors (Ben-Dor et al., 2013) made this technology accessible for the mapping of soil properties using airborne and spaceborne platforms (Ben-Dor, 2002; Ben-Dor et al., 2006; Casa et al., 2013; Goidts and van Wesemael, 2007; Hbirkou et al., 2012; Hill et al., 2010; Stevens et al., 2010). Whereas soil entity is described by the entire profile characteristics, the upper surface, that serves as an interface between the soil body and the atmosphere, is the most important layer (Brady and Weil, 1996) that governs the soil formation process (Jenny, 1941). Passive remote sensing in general and HSR in particular measure the upper surface only (up to 50μm (Ben-Dor et al., 1999)) and hence capture only the soil–atmosphere interface process. Although the upper soil surface cannot directly project the entire soil profile, spectral measurement of the soil surface enables a basic and primarily spatial understanding of the soil entity (Stoner and Baumgardner, 1981). However, in some cases, the soil surface and the soil profile can react differently to their surroundings (Milne, 1936).

The advent of the new technologies and the need for effective soil mapping led McBratney et al. (2003) to propose a new framework of factors (an error predictor and the scorpan predictor) as part of the digital soil mapping system. These factors are generalization of Jenny's five factors (Jenny, 1941) and include soil, climate, organisms, topography,

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*Abbreviations:* HSR, hyperspectral remote sensing; IS, imaging spectroscopy; EnMAP, environmental mapping and analysis program; HyspIRI, Hyperspectral Infrared Imager; HISUI, Hyperspectral Imager Suite; SNR, signal to noise; SORT, spectral overlapping threshold; CVA, change vector analysis; ASDT, automatic selection of the decision threshold; STAR, spectral thresholding approach for registration errors; ROC, receiver operating characteristic; $P_{fa}$, probability of false alarm; $P_d$, probability of detection; FA, number of false alarms; MD, number of undetected change pixels also called missed detection pixels; OE, number of overall error pixels; VNIR, visible near infrared; SWIR, the short-wave infrared; WRB, World Reference Base for Soil Resources; USDA, United States Department of Agriculture.

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parent matter, age and geographic position. By using this framework we are able to produce digital soil maps in a standardized procedure. Deviations in one of the scorpan factors may result in a large error predictor of the digital soil map. Thus, there is a need to update the scorpan factors and the resulting digital soil map of the framework when a change in one of the factors is detected. In particular, changes in short-term soil surface as opposed to long-term soil profile are major elements in this framework to be considered and updated.

Whereas soil profile can change over a long time period (tens to thousands of years), the changes in the soil surface can occur over a short time period, due to the environmental interactions and impacts of the soil components with the atmosphere, pedosphere and antroposphere (Jenny, 1941). Thus, it is important to track the soil surface changes on a temporal basis to pinpoint current soil processes that can affect the long-term soil formation process and dynamics. According to Ong (2013), this kind of work is apparently absent and the temporal resolution domain has not yet been used properly by the HSR community. In practice, the spectral resolution is playing the most dominant role in the HSR arena whereas the temporal resolution has been left behind. Temporal–spectral analysis can spot information about the interaction between the soil surface and the surrounding environment and accordingly can establish a better view of the factors affecting soil formation (Jenny, 1941). Rapid changes in soil surface can occur from erosion, deposition, physical arrangement and self-segregation and man-made activity (Lemos and Lutz, 1957). More specifically, the thin, upper soil layer (that is eventually sensed by optical sensors) may be affected by dust accumulation (Offer and Goossens, 2001), rust formation (Ona-Nguema et al., 2002), plowing activity (Fu et al., 2000), changes in particle size distribution (Sertsu and Sánchez, 1978), vegetation coverage (Zhou et al., 2006), litter occurrences (Frey et al., 2003), and formation of physical and biogenic crusts (Bresson and Boiffin, 1990; Karnieli et al., 1999; Valentin and Bresson, 1992).

Until recently, applications of HSR temporal data were scarce, mainly due to the high cost of data acquisition. In the coming years, this situation will change dramatically, since many satellite HSR sensors are about to be launched (Ben-Dor et al., 2013). Among them are the environmental mapping and analysis program (EnMAP) (Kaufmann et al., 2006), the Hyperspectral Infrared Imager (HyspIRI) (Roberts et al., 2012) and the Hyperspectral Imager Suite (HISUI) (Iwasaki et al., 2011). As a result, the scientific community is starting to perform controlled experiments (Buddenbaum et al., 2012) that will enable the remote sensing community to benefit from the temporal/spectral/spatial data from this technology as soon as it is available.

To combine a temporal domain study with the spatial/spectral domains that the HSR provides, it is important to study this combination under controlled HSR conditions. These conditions should employ a stable sensing capacity (camera and lightning), absence of atmosphere and well-known and uniform soil samples. Airborne and spaceborne HSR systems involve uncertainties such as spatial non-uniformity (Fuller et al., 1994; Muller et al., 1998; Schlapfer et al., 1998), spectral remains from non-accurate atmospheric correction (Ben-Dor et al., 2009; Richter and Schlapfer, 2002), low signal to noise (SNR) performance relative to the laboratory, poor stability and significant illumination effects. As the soil spectrum is relatively continuous and similar along the various soil types, it is challenging to detect spectral changes, therefore the study of spatial/spectral/temporal aspects in soil is first examined under conditions where the above factors are controlled. Accordingly, the current study was conducted under controlled laboratory conditions (absence of atmosphere, high SNR, excellent sensor stability and a stable illumination source) and uniform well-known soil samples. The purpose of this study is to examine the capability to detect soil surface changes using hyperspectral cameras in laboratory conditions with unsupervised change detection techniques. This will set the ground for ongoing scientific temporal monitoring and mapping of soils on planet earth that will become feasible in the next few years with the launch of several hyperspectral satellite sensors.

## 2. Materials and methods

### 2.1. Laboratory setup

#### 2.1.1. Hyperspectral cameras used in this study

The images in this study were recorded using two different hyperspectral HySpex (Norsk Elektro Optikk (NEO), Norway) cameras. A HySpex VNIR-1600 and a HySpex SWIR-320m-e camera. Both cameras were positioned about 1 m above the soil samples. The cameras were set up in a laboratory frame with two tungsten halogen light sources illuminating the sample from about 50 cm distance and at an angle of about 45° in front of and behind the camera.

The HySpex VNIR-1600 camera recorded 1600 pixels across track with a field of view of 17°. The pixel instantaneous field of view was 0.18 mrad across track and 0.36 mrad along track resulting in a single pixel size of 0.0187 cm (the $\gamma$ axis different field of view was compensated by a synchronized acquisition time and soil samples conveyer speed). The recorded images consisted of 1615 image lines and 160 spectral bands in the spectral range of 415 to 992 nm with a spectral sampling distance of 3.7 nm. The data was recorded in 12 bit radiometric resolution.

The HySpex SWIR-320m-e camera recorded 320 pixels across track with a field of view of 13.5°. The pixel instantaneous field of view was 0.75 mrad across and along track resulting in a single pixel of 0.075 cm in both $x$ and $y$ axes. The recorded image consisted of 410 image lines and 256 spectral bands in the spectral range of 967 to 2499 nm with an average spectral sampling distance of 6 nm. The data was recorded in 14 bit radiometric resolution.

A certified reflectance standard white reference panel of known reflectivity (Spectralon) was recorded with each image. The soil samples were placed on a tray that was positioned on an automatic conveyer which was controlled by the NEO software and was synchronized with the HySpex camera recording to achieve a final image with approximately square pixels. The VNIR and SWIR images were taken separately but from the same position above the soil samples.

#### 2.1.2. Soil samples

The soil samples that were used in this experiment were comprised of 69 different soil samples and covered the arid and semiarid climate zone of Israel. All samples were collected from the upper 0–5 cm of the soil surface, brought to the laboratory, and air dried at room temperature and quantitatively grinded to a 2 mm sieve size (Ben-Dor and Banin, 1994). The samples were chemically analyzed by standard methods (Jackson, 1958) for the following properties: clay, silt, average soil particle fraction size, organic matter, iron oxides and calcium carbonate. The clay and silt content were obtained by the hydrometer method (Gee et al., 1986), the soil average sieve fraction size analysis was computed by the average of the six following sieves: 2.0–1.4 mm, 1.4–1.0 mm, 1.0–0.5 mm, 0.5–0.25 mm, 0.25–0.1 mm, <0.1 mm (Ben-Dor and Banin, 1994), the organic matter by loss-on-ignition method (Ben-Dor and Banin, 1989), the iron oxide by the method developed by (Mehra and Jackson (1960) and calcium carbonate by the gasometric method (Nelson, 1982). All samples were given a label using one or two English capital letters and a number (representing the soil clarification according to a local system (Rabikovitz, 1981)) as shown in Table 1. The soils were placed on a flat tray where each sample filled a rectangular cup (2.0 cm × 2.5 cm). All 48 cups together form a soil matrix (tray 1 with four columns and twelve rows (Fig. 1(a))). In each cup, the soil sample was homogenized and the surface was lightly flattened. Every slot location in the grid is recognized with a lowercase English letter indicating its vertical position and a number indicating its horizontal position on the grid (Fig. 1(c) and (d)).

#### 2.1.3. Change detection experiment setup

The soil change experiment was conducted as follows. First, the original arrangement of soil samples as shown in Fig. 1(a) was recorded