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Integration of in situ measured soil status and remotely sensed hyperspectral data to improve plant production system monitoring: Concept, perspectives and limitations

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ABSTRACT

A common problem in agricultural remote sensing is the sub-pixel spectral contribution of background soils, weeds and shadows which impedes the effectiveness of spectral vegetation indices to monitor site-specific variations in crop condition. To address this mixture problem, the present study combines in situ measured soil status and remotely sensed hyperspectral data in an alternative spectral unmixing algorithm. The model driven approach, referred to as Soil Modeling Mixture Analysis (SMMA), combines a general soil reflectance model and a modified spectral mixture model providing as such the opportunity to simultaneously extract the sub-pixel cover fractions and spectral characteristics of crops. The robustness of the approach was extensively tested using ray-tracer data (PBRT) from a virtual orchard, and results showed an improved monitoring of the crop's chlorophyll, water content and Leaf Area Index (LAI). A significant increase in the R^2 between vegetation indices and the biophysical parameters was observed when index values were calculated from the *pure* vegetation signals as extracted by SMMA as opposed to index values calculated from the original (mixed) image pixels (GM1: $\Delta R^2 = 0.19$; MDWI: $\Delta R^2 = 0.38$; sLAIDI: $\Delta R^2 = 0.14$).

1. Introduction

During the last 50 years, agricultural production strategies have changed dramatically, mostly due to economic decisions to reduce the inputs and maximize the profits, and due to environmental guidelines for a more efficient and safer use of chemicals (Pinter et al., 2003). Perhaps the most significant change is the shift towards precision, or site-specific, crop management. Within-field variability is taken into account to optimize the management practices. This requires accurate and consistent information on soil and plant conditions across the farm, and at temporal and spatial scales that match rapidly evolving capabilities to vary cultural procedures, irrigations, and agrochemical inputs (Dorigo et al., 2007; Pinter et al., 2003). An emerging technology in precision agriculture to provide this information is hyperspectral remote sensing (Dorigo et al., 2007; Zarco-Tejada et al., 2004). Hyperspectral data contains valuable information with respect to the physical and chemical properties of surface targets. Moreover, when hyperspectral remote sensing is applied with a high temporal resolution – by sensors on-board of satellites – intensive monitoring of biophysical and biochemical crop characteristics during growth can become a reality, through for instance the use of vegetation indices (Zarco-Tejada et al., 2004) or through radiative transfer model inversions (Jacquemoud et al., 2009). Above ground biomass (Clevers et al., 2007), canopy chlorophyll content (Zarco-Tejada et al., 2004), leaf equivalent water thickness (Eitel et al., 2006), Leaf Area Index (LAI, Delalieux et al., 2008) and leaf nutrient status (Hansen & Schjoerring, 2003) are only a few of the biophysical attributes that have successfully been monitored using features derived from hyperspectral observations.

Aforementioned examples reveal the huge potential of hyperspectral satellite observations for plant production system management. This is also reflected in the mission statements of the upcoming hyperspectral satellites. For the Environmental Mapping and Analysis Program (EnMAP), the main objective is "to investigate a wide range of ecosystem parameters encompassing agriculture, forestry, soil and geological environments, coastal zones and inland waters" (Environmental Mapping & Analysis Program, 2012). The Canadian Hyperspectral Environment and Resources Observer (HERO) states it as "provide the Hyperspectral user community with high quality information on the surface of the Earth, specifically the plants and materials that cover it and their changes with time" (MDA corporation, 2012).

Yet, present-day input parameters provided by hyperspectral satellite observations are not adequate enough. Spectral reflectance distortions caused by the atmosphere and the considerable orbital height of satellites (roughly ranging between 650 and 800 km) drastically impact image interpretation (Brown, 1992). Most of these

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distortions can be corrected for by geometric, radiometric and atmospheric algorithms (Biliouris et al., 2009; Itten & Meyer, 1993). Yet, a persisting issue is the mixture problem associated with the composite nature of pixels (Adams et al., 1993). Because of the large observation height, in combination with the high spectral resolution of hyperspectral satellites, the size of an image pixel is considerable. All current (i.e. Hyperion) and upcoming (e.g. HERO, EnMAP, TAIKI HSC-III) hyperspectral satellites have a spatial resolution of 30 m. It exceeds in many cases the size of the objects of interest. Consequently, the reflectance signal of a pixel is the integrated result of spectral contributions of different subpixel elements building up a pixel. This constrains the accuracy of spectral analysis based on vegetation index development or other feature extraction techniques (Roberts et al., 1993). The mixture problem is also aggravated in agricultural image scenes where mixed pixels prevail because of the discontinuous open canopies typical for most (perennial) cropping systems (Peddle & Smith, 2005). In Fig. 1, this is demonstrated by showing a high resolution aerial image of a citrus orchard. A 30 by 30 m pixel grid is superimposed to illustrate that the reflectance of most satellite pixels in an agricultural image scene cannot be simply interpreted in terms of crop properties only. For most pixels, subpixel mixing of soils and/or shadows occurs.

In more traditional plant system monitoring studies using (spaceborne) remote sensing, the mixing problem is often ignored or rather superficially dealt with. The majority of available unmixing algorithms are focused on roughly estimating the proportional ground cover of the vegetation class in a mixed pixel (e.g. Quarmby et al., 1992; Asner & Heidebrecht, 1992; Lobell & Asner, 2004; Fitzgerald et al., 2005; Peddle & Smith, 2005; Somers et al., 2009a). This technique, hereafter referred to as Area Unmixing (AU), is popular for the rapid, early and low-cost assessment of crop area statistics from multi-temporal and -spectral low (spatial) resolution imagery (Verbeiren et al., 2008), but the technique is clearly unable to extract spectrally 'pure' vegetation characteristics, uncontaminated by pixel components, such as soil and shadow.

Several authors dealt with this problem partially by adjusting existing vegetation indices, in particular the Normalized Difference VI (Tucker, 1979) and the Simple Ratio (Jordan, 1969) indices, to make them more robust for soil background effects. The basic assumption of these soil-adjusted vegetation indices is that soils are characterized by a unique linear relationship between NIR (700–1350 nm) and VIS (400–700 nm) reflectance, i.e., the soil line. Huete (1988) adapted the formula of NDVI by including the coefficients of the soil line in the Soil-Adjusted Vegetation Index (SAVI). The transformed (TSAVI; Baret & Guyot, 1991), modified (MSAVI; Qi et al., 1994) and optimized SAVI (OSAVI; Rondeaux et al., 1996) are all variants of the traditional SAVI. Despite these efforts, the success of the soil-adjusted indices is limited because the soil line is not as generic as assumed while the technique is mainly restricted to corrections in the VIS–NIR spectral domain (Delalieux et al., 2008; Rondeaux et al., 1996).

An accurate monitoring method for critical crop production parameters, however, requires the removal of undesired spectral background effects from mixed image pixels. Consequently, a more generic approach to reduce subpixel background effects is needed allowing the accurate and site-specific monitoring of plant production systems. Tits et al. (in press) proposed a Signal Unmixing (SU) methodology to extract the 'pure' vegetation signal from a mixed pixel signal consisting of soils and vegetation. Using an extensive spectral library for each endmember, a Multiple Endmember Spectral Mixture Analysis (MESMA, Roberts et al., 1998) approach was used to evaluate different endmember combinations, selecting the endmember combination with the lowest modeling error as the spectral signatures of the components in the pixel. Two major limitations of the MESMA methodology are (i) the requirement of large libraries to encompass the spectral variability that can be expected to occur in the field, and (ii) ill-posedness effects resulting in multiple endmember combinations that produce the same mixed spectrum (Tits et al., in press). However, results showed that the performance of the SU model improved significantly with increasing knowledge on the soil endmember, as it minimizes the two difficulties described above.

In this study we hypothesize that the integration of in situ measured soil status data and remotely sensed hyperspectral data can provide the needed information to estimate the spectral signature of the soil endmember, so that the subpixel vegetation reflectance signature can be extracted from the mixed image pixels. Previous studies have already demonstrated the added value of combining remote sensing and in situ data inputs for improved image interpretation. Examples for more general applications are the vicarious calibration of sensors (Dinguirard & Slater, 1999) and the atmospheric correction of satellite images using the invariant-object method (Liang et al., 2001). In situ data is also used in combination with remotely sensed spectral data in applications such as climatology (Reynolds et al., 2002), sediment transportation (Ouillon et al., 2004) and agriculture (Dzikiti et al., 2010). Both Kerr and Ostrovsky (2003) and Zaks and Kucharik (2011) state that a combination of field measurements and remote sensing is needed to solve the problem of scale mismatch between field data and most remote sensing data sources. The same principle is used in this study to introduce a SU technique to remove soil background and shadow effects from optical satellite images. The proposed concept consists of the assimilation of soil reflectance models (Müller & Décamps, 2001; Somers et al., 2009c, 2010) and Spectral Mixture Analysis (SMA; Adams et al.,

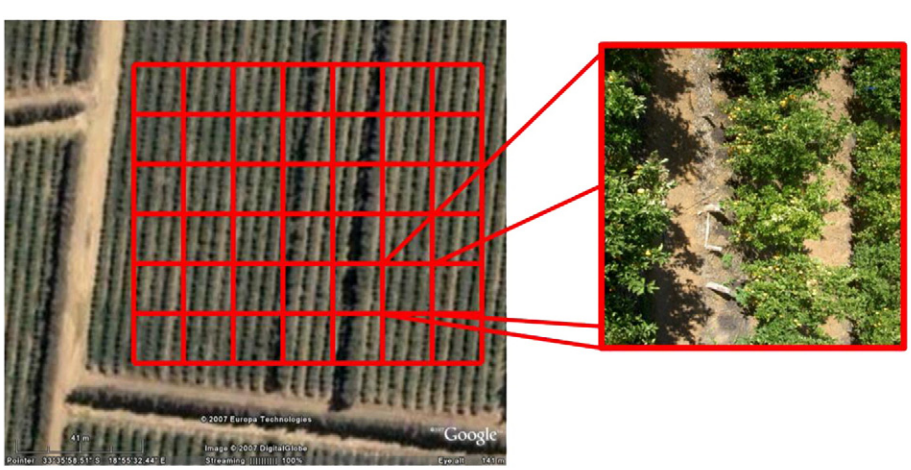

Fig. 1. Example of a 30 by 30 m grid over a high resolution image, combined with a detail of a pixel to illustrate the mixed nature of the pixel.
Adapted from Somers (2009d).