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Discriminating and mapping soil variability with hyperspectral reflectance data

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Abstract

The classification and mapping of soils and soil variability is important for a variety of environmental and agricultural applications. Advances in precision agriculture, better understanding of environmental processes and improvements in mathematical models used to predict and understand landscape phenomena all require detailed information about soils at increasingly finer scales. The goal of this thesis was to address this need for fine scale soil information by developing new mapping methodologies from hyperspectral remote sensing and reflectance spectroscopy. The spatially continuous and rich spectral information of hyperspectral data provides a powerful diagnostic tool for mapping and monitoring the earth's surface materials. Similarly, reflectance spectroscopy allows for rapid and cost effective measurement of materials based on their spectral response. These two technologies offer the potential to record information about soils and provide fine scale or continuous surface information for natural resource management.

The research aimed to explore the extent to which variation in surface horizon soils could be discriminated and mapped with hyperspectral reflectance data. The study examined the prediction of soil properties and classes with spectroscopic measurements, the mapping of surface soils through interpolation from sample sites and the analysis of hyperspectral imagery. The influence of vegetative cover and soil type on the identification of soil class and quantification of soil exposure was investigated using simulated imagery. Each of the research components focused on the soil properties and range of variation typically encountered in southern Australian agricultural regions.

Reflectance spectroscopy was used to discriminate select field soil survey classes and to predict and quantify various laboratory derived soil properties. For both of these analyses visible near-infrared reflectance spectra (350 – 2500 nm) were collected with an ASD FieldSpec Pro using a hand held probe. The spectral separability of the commonly used field survey classes texture, carbonate and Munsell colour (separated into hue, value and chroma) was assessed using penalised discriminant analysis. Only Munsell chroma was adequately discriminated; while other classes showed some separability, it was limited and not sufficient for soil classification. Failure to adequately classify the soil property classes

was attributed to the subjective nature of the field survey methods, as well as co-variance between soil properties.

Quantitative prediction of laboratory-measured soil properties (clay, organic carbon, iron oxide and carbonate) from reflectance spectra was conducted using partial least squares regression. Clay and carbonate contents were the best predicted, although predictions of iron oxide and organic carbon were also acceptable. The utility of reflectance spectroscopy to provide inputs for soil mapping was assessed by comparison of kriged surfaces of soil properties. This comparison indicated that the methodology captured the same variability in the landscape over the same range in values for each of the soil properties.

Prediction of soil exposure and type through vegetation cover was assessed with two types of simulated imagery which were created using spectra of soil, photosynthetic and non-photosynthetic vegetation. Both simulated images had the same, known combinations of soil and vegetation but the relative mixes were created differently. Soil and vegetation cover fractions were retrieved from the images through linear spectral unmixing and compared with the measured fractions. Soils were accurately identified and classified in both image types. However, not all soil spectra were isolated from mixed pixels equally or successfully to provide accurate abundance fractions: some spectral mixes of soil and vegetation were incorrectly classified as different soils, highlighting potential sources of error in unmixing procedures.

The mapping of surface soils was assessed using image derived soil endmembers and HyMap hyperspectral image data. Endmembers were isolated from the imagery using a pixel purity process before being used in a partial unmixing routine. Field estimates of soil exposure and laboratory analysis of soil samples were correlated with unmixing abundances and used to characterise areas mapped by the different soil endmembers. Only a moderate correlation between the field and image derived soil exposure was found. Furthermore, soil properties for the different endmembers showed little difference between classes and the mean of all samples. However, more than 70% of the areas mapped by the four endmembers were unique, indicating that they were spatially distinct. These results imply that the spectral response of soils captured by the hyperspectral imagery is more strongly influenced by land management and soil properties other than those determined through laboratory analysis.

Reflectance spectroscopy of surface samples offers the potential to quickly and reliably predict soil properties. Results indicate that it can be applied successfully to local geographic areas and interpolated with geostatistics to create maps. The mapping of soils with hyperspectral data presents problems that stem both from issues of plant material obscuring the soil surface and high variability in soil reflectance due to management and landscape processes. The unmixing of soils and vegetation (photosynthetic and non-photosynthetic) from simulated imagery was successful but showed the potential for mixed pixels to be confused for non-target soils. Similarly, landscape and management processes are subject to high variability and are not necessarily related to soil properties relevant to agricultural and environmental applications. To fully utilise remote sensing for mapping soils in a natural environment further research is required.

Declaration

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Refereed publications

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Proportion of contribution by author

This is a declaration of the extent of each author's contributions to the refereed papers arising from this thesis. The extent of each of author's contribution is quantified for conceptualisation, realisation and documentation. Each author gives permission for the paper containing their contribution to be included in this thesis.

Percent contribution and permission to include paper in this thesis:

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	Conceptualisation	Realisation	Documentation	Signature
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Lewis, M.	10%	5%	10%	_____
Ostendorf, B.	5%	2.5%	2.5%	_____
Chittleborough, D.	5%	2.5%	2.5%	_____

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