Identifying spatial variability of subsoil constraints using multiyear remote sensing and electromagnetic induction

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Abstract
Subsoil constraints are important growth limiting factors in many soils of north-eastern Australia as they reduce the ability of roots to obtain water and nutrients. However, accurate information on the variability of subsoil constraints across the landscape is difficult to obtain. We developed an empirical-statistical model using historical wheat yield data, remotely sensed (Landsat) imagery and in-crop rainfall to estimate yield variability at sub-paddock scale to accurately identify areas suspected of subsoil constraints at farm scale. The yield predictions for 16 paddocks where wheat crops were grown during 2000-08 showed reasonably good agreement with farmer-reported yield ($r^2 = 0.50$). Analysis of the yield predictions showed 53% of the farm area exhibited consistently low yield, indicating the presence of at least one yield constraining factor. Soil samples averaged for low-yielding areas had substantially high concentrations of chloride in subsoil, high exchangeable sodium percent in the surface and subsoil and high nitrate nitrogen and volumetric moisture in the profile as compared to high-yielding areas. The results suggest that the paddocks or areas of paddocks exhibiting consistently low yields are an indicator of the presence of yield-limited factor/s. This offers the potential to map suspected areas of subsoil constraints.

Key Words
Subsoil constraints, Landsat, spatial variability, remote sensing.

Introduction
Salinity, sodicity, acidity and phytotoxic concentrations of chloride (Cl) in subsoils are major constraints to crop production in many soils of north-eastern Australia because they reduce the ability of crop roots to extract water and nutrients (Dang *et al.* 2006). Among subsoil constraints, subsoil Cl concentrations have a greater effect in reducing soil water extraction in the subsoil (Dang *et al.* 2008). Subsoil constraints vary both spatially across the landscape and vertically within soil profiles. Grid sampling to identify the distribution of possible subsoil constraints, both spatially across the landscape and within the soil profile, is time-consuming and expensive.

Crop yield mapping provides high-resolution estimates of spatially varying crop production; however, the adoption of yield mapping in Australia has varied (Jochinke *et al.* 2007), such that the detailed information is only patchy. Recent developments in sensing technologies have shown promise for quantifying soil and crop yield variations both within and between agricultural fields (Fisher *et al.* 2009). The potential advantages of remotely sensed images are: (i) the ability to bypass field measurements of yield; (ii) the ability to estimate yield at a range of spatial scales, thus eliminating sampling error within field variability; and, (iii) the availability of archived imagery thus enabling analysis of past growing seasons that may not have recorded yield (Lobell *et al.* 2007). Further, surrogate yield information may be generated from satellite images, allowing extrapolation to broader scales. Australia has more than 25 years of historical Landsat satellite data available. There is potential to increase the quantity and quality of spatial data needed to identify causes of spatial and temporal variability in cropping areas. We, therefore, attempted to develop an empirical-statistical model to predict yield variability at sub-paddock scale. This would determine consistently low yielding areas, and indicate the presence of a subsoil constraint.

Methods
We used historical mid-season normalised difference vegetation index (NDVI), generated from Landsat imagery to simulate wheat grain yield for a 3240-ha farm near Goondiwindi in southern Queensland, Australia (28° 19' S and 150° 30' E). In this area, wheat crops are generally sown in May. Anthesis is around mid-September, and crops are harvested during October. Long-term average annual rainfall for the area is 617 mm and average in-crop rainfall (May-October) is 225 mm. The climate of the region is semi-arid with

high potential evapotranspiration (1300-2200 mm per annum) (Webb *et al.* 1997). The common soil types of the farm are grey and brown Vertosols (Isbell 1996).

Site-specific yield data, available for 31 out of 55 wheat crops grown in 16 paddocks during 2000-2008, were accessed from the farmer, who collected yield data at harvest using AgLeader yield-monitoring equipment, linked to a differentially corrected GPS. Each field dataset was passed through several cleaning algorithms to remove erroneous yield associated with harvester dynamics, speed change, overlaps and turns. The clean yield data for each paddock and season was spatially interpolated with block kriging at the nodes of a 25-m grid, with 20-m blocks, using the Vesper software (Whelan *et al.* 2001). Cloud-free images of Landsat 5 TM (Thematic Mapper) and Landsat TM 7 ETM+ (Enhanced Thematic Mapper) satellite sensors were acquired close to anthesis. All images were geometrically and radiometrically corrected. The locations of each paddock boundary were identified on the satellite image, and the NDVI transformations were obtained for each crop where a wheat crop was grown during 2000-2008. For each node of the 25x25 m grain yield grid, the NDVI values were obtained using nearest neighbour interpolation.

A random selection of 5% of the data was used to develop the relationship between grain yield and NDVI and the in-crop rainfall before acquiring landsat (ICR-BL) image:

Grain yield = 1.1347 NDVI + 0.01389 ICR-BL; $r^2 = 0.72$, $P = 0.00001$, RMSE = 0.39   (1)

Grain yields were estimated in each year for each pixel using multiple linear regression equation between header yield and NDVI and validated with farmer-reported yield for wheat crops grown during 2000-2008. For estimating field-average surface and subsoil constraints, we performed survey using Geonics EM38® in vertical dipole mode to map apparent electrical conductivity (EC_a) levels. Soil cores to 1.5 m depth and separated in 8 depth intervals were taken at selected points as determined from EC_a surveys and analysed for physical and chemical properties (Dang *et al.* 2009). Soil pH, EC, Cl and NO_3-N were determined in 1:5 soil:water suspension. Electrical conductivity of saturation extracts (EC_{se}) was calculated from EC (1:5 soil:H_2O), Cl and clay content using the method of Shaw (1999). Cation exchange capacity (CEC) and exchangeable cations were determined using a 1M NH_4Cl (pH 8.5) extracting solution (Rayment and Higginson 1992). Prior to extraction, soluble salts were removed by pre-washing with 60% aqueous alcohol. The extracts were analysed for exchangeable cations on inductively coupled plasma-optical emission spectrometer. Exchangeable sodium percent (ESP) was calculated as ratio of exchangeable Na^+ to CEC. To identify areas suspected of subsoil constraints, the predicted yield images for each year were converted to percentiles, with 0 and 100% corresponding to minimum and maximum estimated yields. The proportion of each paddock that exhibited consistently low yields was compared with the proportion expected by chance at 80th percentile (Lobell *et al.* 2007).

Results
Spatial variability of subsoil constraints
Across locations, average Cl concentrations, EC_{se}, and ESP increased with soil depth where as soil pH increased to 0.2 m and decreased at depth (Figure 1). Across locations at different depths, average Cl ranged from 49 to 1092 mg/kg to a depth of 1.5 m and EC_{se} ranged from 0.71 to 6.71 dS/m. Compared to Cl concentration, vertically averaged ECse was more spatially variable which was primarily due to the presence of gypsum at depth.
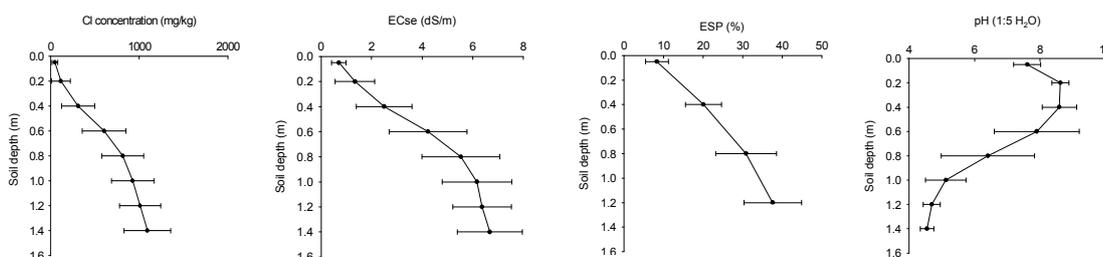
Figure 1. Average Cl concentration, electrical conductivity of saturated extract, exchangeable sodium percent, and soil pH with depth across whole farm. Error bars represent standard deviation.

Across locations, ESP ranged from 8 to 37% and soil pH ranged from 7.6 to 4.5 to 1.5 m and was more spatially variable than ESP at depth. Most of these soils were found to be saline ($EC_{se} > 4.0$ dS/m) below 0.5

m depth, sodic (ESP ≥ 6%) below 0.1 m depth, and had potentially phytotoxic levels of Cl (> 600 mg/kg) below 0.5 m depth (Northcote and Skene 1972; Shaw, 1999; Dang *et al.* 2008).

Yield estimation
The Landsat-based yield estimates of 16 paddocks where wheat crops were grown during 2000-2008 showed reasonably good agreement with farmer-reported yield. Most of the values were near 1:1 line (Figure 2a). This relationship was further improved by using average yield estimate across all seasons-years and average farmer-reported yield for all seasons (Figure 2b) suggesting that use of single year of yield data or satellite image would not be enough to predict consistently low or high yielding areas of the paddock.
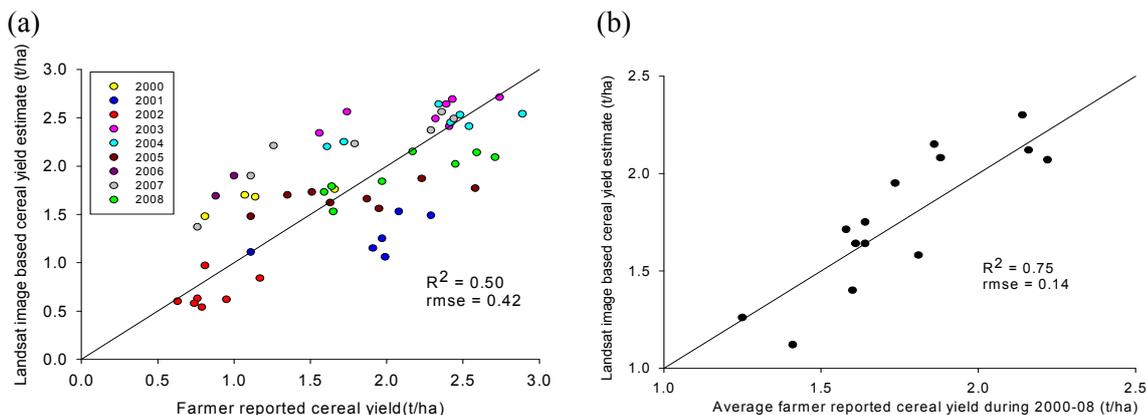
Figure 2. Comparison of Landsat-based wheat yields for 16 paddocks during 2000-08 with farmer-reported yields (a) for individual seasons, and (b) average of all seasons.

Identifying spatial variability of subsoil constraints
Using a threshold p = 80%, significantly more pixels never exceeded the threshold than would be expected by chance (Figure 3a), indicating the presence of a yield constraining factor. Fifty-three percent of the area never reached the 80th yield percentile (Figure 3b).
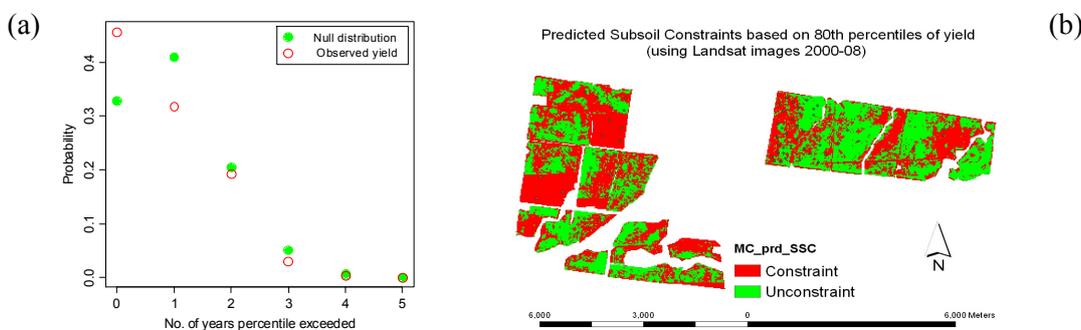
Figure 3. (a) Probability of pixel exceeding 80th percentile of yield, and (b) predicted subsoil constraints, for the entire farm.

Soil from unconstraint areas had substantially high concentrations of Cl in subsoil, high NO_3-N, volumetric moisture in the profile and high ESP in the surface soil as compared to constraint areas (Figure 4). High Cl in the subsoil restricts the ability of the roots to extract moisture and nutrients from subsoil, high ESP in surface soil results in soil crusting, water-logging, and poor germination. The presence of unused NO_3-N and moisture in the soil profile results in economic losses and environmental degradation (Dang *et al.* 2006).
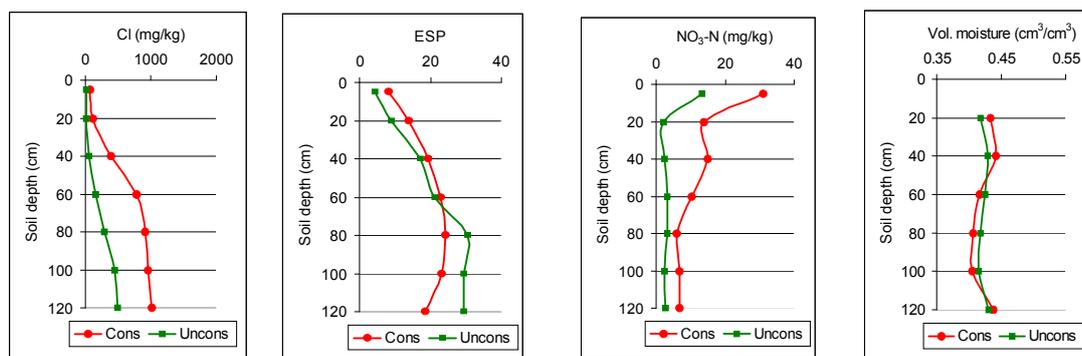
Figure 4. Comparison of Cl, ESP, NO₃-N, and volumetric moisture in constraint and unconstraint areas of the farm.

Conclusion

In cropped fields, sub-regions of low yield, consistent for several growing season, suggest the presence of a soil-related constraint. The techniques developed offer an opportunity to identify within-field spatial and temporal variability using satellite imagery as a surrogate measure of grain yield. The resulting information is directly useful for a farmer wanting to improve management spatially. It also helps stimulate further research hypotheses about the influence of soil variability on crop yield.

Acknowledgments

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