Potential of dual gamma-ray and electromagnetic induction sensors to map soil type and plant available water capacity

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Abstract
Plant available water capacity (PAWC) is used to simulate crop yield, fertiliser requirement and leaching at point and field scales. Rules based on the grower and agronomist's knowledge and on few samples are currently available to integrate electromagnetic induction (EMI) and gamma-ray data and estimate soil type and PAWC spatially. This approach is slow and impractical to apply to large number of fields. Our aim was to use classification and regression tree (CART) to analyse the geophysical data and arrive at statistically sound rules to classify soil type and PAWC. CART analysis was performed on 122 soil profile PAWC and geophysical data from the Esperance region of Western Australia (WA). Nine soil types were identified in Esperance and CART arrived at 12 rules to attribute these soils to 8 soil types. The arbitrary nature of soil type classification commonly used in WA led to confusion in CART predictions. CART sometimes misclassified soils to a similar soil type. The predicted classes were better matched when soils were grouped to a higher level of classification. This avoided over-classification that was not justified by differences in geophysical properties. The link between soil type and PAWC was however tenuous as variation in PAWC within a soil type was often greater than its variation between soil types.

Key Words
CART, geophysics, digital soil sensing, soil water, classification, spatial variation

Introduction
Plant available soil water storage capacity (PAWC) interacts with seasonal rainfall to govern spatial and temporal variations in potential grain yield in water-limited environments (Wong and Asseng, 2006; Lawes et al., 2009). Modelling this interaction allows us to estimate site and season specific yields and fertiliser requirements to maximise profits (Lawes and Robertson 2011). It also allows us to identify areas that drain the most water and nutrients and poor performing yield areas (Wong et al., 2006). PAWC often varies by 100mm across the field because of variation in soil type and root depth. In some seasons this generates a 1t/ha variation in grain yields (Lawes et al 2009; Wong and Asseng, 2006).

Direct measurement of PAWC is time consuming and prohibitive. Wong et al., (2010) developed rules to identify soil types and ultimately PAWC based on expert interpretation of EMI and gamma-ray data. These rules enabled EMI and gamma-ray data to be transparently integrated to predict soil type and PAWC. Relationships between EMI, gamma-radiometric data and PAWC are unlikely to be linear and interactions may occur at different levels. Given these constraints, there is a need to develop a statistically sound optimal rule set from a more substantial set of data. Classification and regression trees (CART) have been used to develop rule sets to map soil types, to estimate individual soil properties and drainage classes. The aim of this work is to improve the efficiency of estimating PAWC spatially by using CART analysis of dual EMI and gamma-radiometric sensor data that may discriminate between soil types and PAWC values.

Methods
Site locations and soil
The main location of work was the southern wheatbelt of WA close to the town of Esperance (about 725 km by road south east of Perth). The climate is Mediterranean-type with hot dry summers and cool wet winters. The average annual rainfall in Esperance is 503 mm of which 335 mm falls in the May to October growing season. The farming system consists of winter cropping in rotation dominated by wheat, barley, canola and lupins with occasional pastures. The Esperance district is broadly divided into a region of sandplain soils to the south and mallee soils to the north (McArthur 2004). Sandplain soils with superficial gravels and boulders are common in the north and west of Esperence. They are often underlain by clay at depths varying from a few centimetres to more than 5 m. Some sands occur as linear dunes with intervening swales that are intermittently waterlogged. The inland sandplain soils consist of sandy and gravelly duplex soils. These soils are arbitrarily termed shallow duplex if the depth to texture contrast <30 cm and deep duplex if the

depth to texture contrast is at 30-80 cm depth. Mallee soils are calcareous at least in the lower horizons and are commonly salt-affected. Salt lakes and associated dunes are common in the area. The top of the landscape is dominated by red earths, clay and sandy loams. Sandy duplex soils occur along valleys.

PAWC measurement and Geophysical survey

One hundred and twenty two soil cores were taken to a maximum depth of 90 cm to measure bulk density and soil water contents at drained upper limit and crop lower limit after harvest across 6 farms. Between 16 and 36 sampling locations were chosen per field/farm to represent high to low gamma-ray emission values. The amount of water (mm) contained between the crop lower limit and the drained upper limit was calculated to give the PAWC of the soil profile. Soil type was determined by hand texturing. Paddocks sampled for PAWC were also surveyed for their geophysical properties. EMI survey used an EM38 instrument with intecoil spacing of 1 m in its vertical dipole mode. This sensed apparent electrical conductivity (EC_a) to an effective depth of 1.5 m. The gamma (γ)-ray survey used an *Exploranium* γ-ray spectrometer which measures γ-radiation from potassium (K), uranium (U), thorium (Th) decay series and from all elements. Gamma-ray emission and EMI surveys were carried out simultaneously using a line spacing of approximately 25 m, a speed of 10–13 km hr^{-1} and a data logging frequency of 1 Hz.

CART analysis

Decision trees can cope with complex data by splitting the classification decision into discrete simple steps. Each step segregates the data into more distinct classes. Each segregation step aims to maximise homogeneity within and differences between classes. The CART analysis used EMI data, γ-radiometric emission from potassium (γ-K), thorium (γ-Th), uranium (γ-U) and from all elements (γ-TC) as predictor variables and soil type as the dependent variables. The reasons for using dual ECa and gamma-radiometric sensor data for this analysis were explained elsewhere (Wong et al., 2010). The rules for inferring soil types were acquired from the measured data through the CART model.

Results and Discussions

Classifying soil types

Textural assessment and classification of the 122 Esperance soil cores identified 9 soil types. There were 31 shallow loamy duplex, 26 shallow sandy duplex, 22 deep sandy duplex, 11 clay, 10 loam, 7 loamy earth, 7 sand, 6 sandy earth and only 2 deep loamy duplex profiles. ECa measurements were uncorrelated with γ-K, γ-Th, γ-U and γ-TC. The CART analysis fitted the geophysical data to 12 terminal nodes (Figure 1). These nodes represent increasingly finer textured soils as we move from left to right. The two deep loamy duplex profiles were not enough for CART to define their soil classification.

The analysis identified unique rules to identify three sandy soils with low EMI and low γ-emission: (1) sand with EC_a <20 mSm^{-1} and γ-Tc<213, (2) sandy earth with EC_a 20-87 mSm^{-1} and γ-K < 6.5 counts and (3) deep sandy duplex with EC_a 20-87 mSm^{-1} and gamma ^{40}K > 6.5 counts (Figure 1). At the other extreme of soil texture, the CART analysis identified a unique rule for a clay soil: high EC_a >173 mSm^{-1}, high γ-Tc > 213 but low γ-Th < 9 counts. The unique rule for a loam is medium EC_a <133 mSm^{-1} high γ-Tc > 460. The loamy earth shares the medium EC_a between <133 mSm^{-1} of a loam but has lower γ-Tc <460 of which γ-K counts >33. Both the shallow sandy duplex and shallow loamy duplex are identified using multiple rules (Figure 1). This suggests that the observed classification of the soil fails to distinguish differences in mineralogy, clay content and actual depth to texture contrast within a soil type. CART analysis identified different geophysical properties within these soil types leading to distinct rules to distinguish between them. Finer texture or shallower depth to texture contrast occurs as we move from left to right of the decision tree.

Because of the arbitrary and qualitative nature of soil type characterisation commonly used in WA, CART performed better when similar soil types were aggregated into to a higher level of classification than the 9 soil types observed. The group of sandy soils characterised by low EMI and γ-ray emission values classified as sand, sandy earth and deep sandy duplex are well identified as a group. This group has 35 members (22 deep sandy duplex, 7 sand and 6 sandy earth) and 86% of the members are correctly allocated to this group (Table 1) using the rule EMI < 87 mSm^{-1} and γ-Tc <213. This low EMI and low gamma rule for sandy soils is the same as that derived from expert knowledge and limited samples (Wong et al., 2010). Within this group of sandy soils, sand is mostly identified as sand but is sometimes confused with deep sandy duplex and sandy earth. Similarly sandy earths are identified as sandy earth but are sometimes confused for sand or deep sandy duplex. Deep sandy duplex was classified correctly on 73% of occasions, and this was higher

than any other individual soil type. However, confusion occurs with another sandy soil (sandy earth), another sandy duplex (shallow sandy duplex) and shallow loamy duplex and loamy earth. Part of the confusion arises from arbitrary definition of soil type: a deep sandy duplex has its texture contrast at 30-80 cm. If this contrast occurs at > 80 cm, the soil is classified as deep sand and if it occurs at < 30 cm, it is classified as shallow sandy duplex. The problem is essentially one of using a high resolution digital soil sensing technique with coarse resolution arbitrary soil classification where depth intervals of 30-80 cm is acceptable but a difference of 1 cm can change the classification of a soil. In spite of this shortcoming, areas with low EMI < 87.0 mSm^{-1} and low γ-Tc <213 can reliably be described as deep sandy soils.

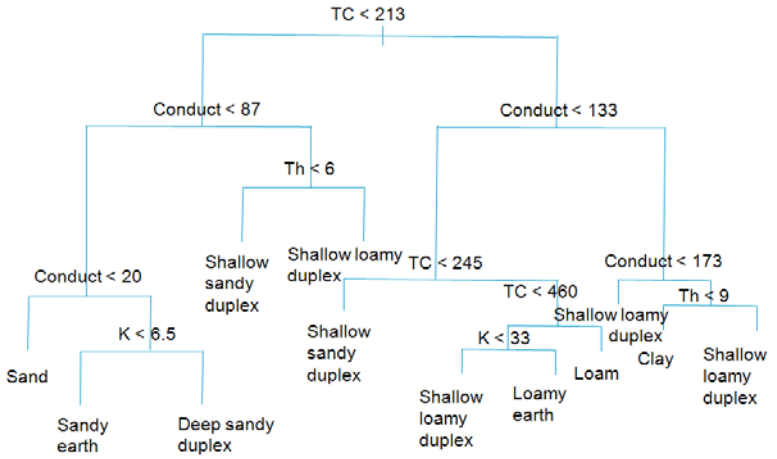

Figure 1. CART Classification of soil types according to their apparent conductivity (EC_a expressed as mSm^{-1}) and gamma-radiometric counts.

The finest textured soils are represented by a group characterised by high γ-Tc > 213 and high EMI > 133 mSm^{-1}. This rule "high EMI and high gamma" is similar to the knowledge-based rule for clay soils (Wong et al., 2010). The clay soil is sometimes confused with a group of shallow loamy duplex which has a clay layer at < 30 cm (Table 1). The depth to texture contrast is shallow in this group of soils. This and the fact that the topsoil is already a fine textured loam leads to some confusion observed between clay and some shallow loamy duplex soils. Given the limitation of arbitrary soil classification, the area with high γ-Tc > 213 and high EMI > 133 mSm^{-1} can be described as an area with fine textured soils with clay at or near to the surface.

Table 1: Contingency table of goodness of group of soil identification by CART. The columns represent the observations and the rows represent the CART predictions.

	Sand	DSD	SE	SSD	Loam	LE	SLD	Clay	DLD	Type 2 error†
Sand	4	0	2	0	0	0	0	0	0	0.23
DSD	2	16	1	9	0	0	0	0	0	
SE	1	1	3	0	0	0	0	0	0	
SSD	0	1	0	11	0	1	4	0	0	0.35
Loam	0	0	0	1	6	1	1	0	1	0.37
LE	0	1	0	0	0	3	2	0	0	
SLD	0	3	0	4	4	2	24	7	1	0.30
Clay	0	0	0	1	0	0	0	4	0	
DLD	0	0	0	0	0	0	0	0	0	N/A
Total	7	22	6	26	10	7	31	11	2	
Type 1 error*	0.14			0.58	0.41		0.17		N/A	

[1]Classification of either observed values (*) or predicted values (†) to wrong classes

The group of loamy soils with observed classes loam and loamy earth occurs at EMI<133 and γ-Tc >245 (Figure 1). The CART analysis classified 59% of the samples in the right classes and 35% were in the broad observed group of shallow loamy duplex. These shallow loamy duplex soils are identified by 4 distinct rules and geophysical properties and it is plausible that the rule EMI<133 and total counts >245 identify those shallow loamy duplex soils that are more aligned with the geophysical properties of the group that we call

"loamy soils". It appears that the CART analysis of the geophysical data is better able to distinguish differences in the broadly defined shallow loamy soils than the soil classification used would allow. If this is the case and the subset of shallow loamy soils are in fact more aligned to loamy soils, then CART analysis is classifying 94% of the samples correctly with a type 1 error of just 6%. The shallow sandy duplex is also well fitted with two rules but its type 1 classification error was high (42% of observed values were in the correct predicted class). For nine of the twenty six members (35% of cases) there was confusion with deep sandy duplex and the likely causes of such confusion due to arbitrary classification of deep and shallow duplex soils are already discussed.

Estimating PAWC

Sand, deep sandy duplex (DSD) and sandy earth (SE) had the lowest median PAWC of 38 -54 mm (Figure 2). This increased to 74 mm for the shallow sandy duplex (SSD) and loam. The loamy earth (LE) had the highest PAWC of 114 mm. PAWC did not increase in profiles with finer textured soils. The shallow loamy duplex (SLD) and clay had a median PAWC of 64 and 73 mm respectively. This is lower than PAWC measured in all but the sandiest textured soils and may be due to inability of roots to explore the soil profile to take up water. Variation in PAWC within a soil type was generally larger than differences in median PAWC values measured between several adjoining soil types shown in Figure 2.

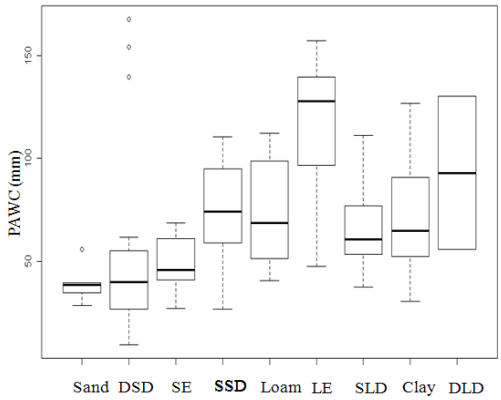

Figure 2. PAWC measured within and between soil types. Box shows 25th and 75th percentiles and median values. Whiskers span 10th and 90th percentiles. Individual points represent outliers.

Conclusions

CART provides a statistically sound approach to analyse continuous quantitative geophysical data and classify soils into significantly different classes. The predicted classes can only be matched if we group observed classification to a higher level than measured to avoid subjective bias and over classification that is not justified by the geophysical properties of the soil. The link between soil type and PAWC was tenuous as PAWC depends on both soil type and the crop's ability to extract water. Variation in PAWC within as soil type was often greater than its variation between soils.

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