SRA Final Report

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Seeing is believing: managing soil variability, improve crop yield, and minimising off site impacts using digital soil mapping

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Honorary Associate Professor John Triantafilis
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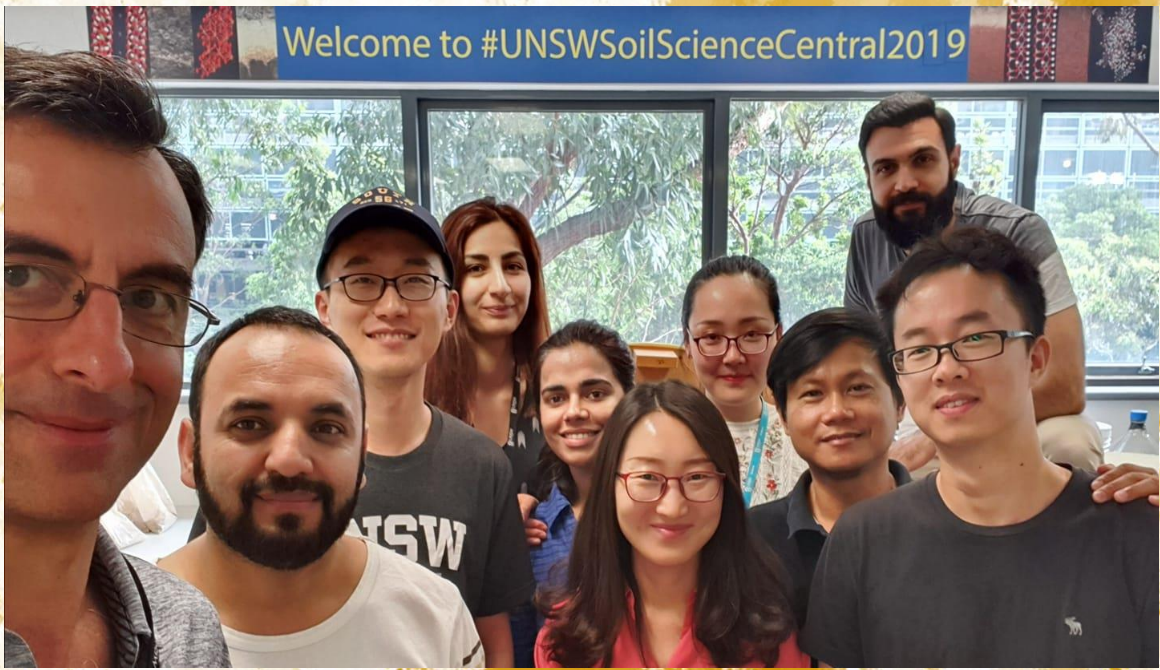

Contact:
John Triantafilis
Telephone: +61 4 3708 7983
Email: j.triantafilis@gmail.com

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1. Executive Summary

Over 70 % of sugarcane industry operates next to the Great Barrier Reef (GBR). Farmers are under pressure to improve practices to minimise off-farm pollution, while at the same time improve fertiliser (e.g. lime) and amelioration (e.g. gypsum) efficiency to minimise yield variation. While the biggest driver of variation is rainfall, differences in soil condition affect yield and farmers need to know its variation.

For example, knowledge about soil cation exchange capacity (CEC – cmol(+)/kg) is important because it is a measure of how many exchangeable (exch.) cations (i.e. calcium [Ca], magnesium [Mg]) can be retained on soil surfaces and because it influences soil stability, nutrient availability, pH and reaction to fertilisers.

If no action is taken to map soil and manage different soil condition, opportunities to sustainably improve application of fertilisers and ameliorants in a cost-effective way will be foregone as well as an opportunity to make a meaningful, economically viable contribution to reducing impacts of sugarcane growing on the GBR.

The **six-easy-steps (6ES) nutrient and ameliorant guidelines** were developed to minimise in-field variation and reduce losses of inputs to the GBR. However, there was and is no practical way for farmers to apply the **6ES guidelines** given there is no in-field data to enable its application. This project aimed to undertake case studies in four sugarcane growing areas to enable precision agriculture via the use of a digital soil map (DSM).

A DSM requires collection of digital data, such as proximally sensed electromagnetic (EM) induction and gamma-ray spectrometry (γ-ray) and coupling this to soil data via mathematical models. The study areas, where a DSM approach was taken, include **Mossman**, **Herbert**, **Burdekin** and **Proserpine**.

The results show that a DSM approach is valid with the potential to implement the **6ES nutrient and ameliorant guidelines** to enable precise application of lime, gypsum and other fertilisers demonstrated via various case studies. They are provided here in brief and in summarised form in **Section 5**. All published papers or submitted manuscripts are provided in the same order and appear in the **Appendices**.

In the **Mossman** area (see **Section 5.1**), a DSM approach was used to characterise soil condition in terms of topsoil (0-0.3 m) soil organic carbon (SOC, %) variation, with the DSM able to be used to apply the **6ES nutrient management guidelines** (Schroeder et al., 2010) with varying N application rates for different levels of SOC to achieve a district yield potential of 120 t/ha after a bare fallow (Wang et al., 2021).

In various areas (see **Section 5.2**), the DSM approach could be used to predict topsoil (0-0.3 m) clay content across any of six study sites in the **Mossman**, **Herbert**, **Burdekin,** and **Proserpine** districts. The site-specific approach to making DSM of topsoil clay was optimal, however site-independent (universal calibration) and a spiking approach give almost as good prediction agreement and accuracy (Arshad et al., 2021).

In the **Herbert** (see **Section 5.3**), a DSM approach was used to characterise soil condition in terms of topsoil (0–0.3 m) and subsoil (0.6–0.9 m) CEC (cmol(+)/kg) variation, with the topsoil DSM able to be used to apply the **6ES nutrient management guidelines** (Sugar Research Australia, 2013) with varying lime application rates for different levels of CEC (Li et al., 2018).

In the **Herbert** (see **Section 5.4**), a DSM approach was used to identify zones by clustering digital data (i.e. EM and γ-ray data). The DSM was more accurate in predicting topsoil (0-0.3 m) and subsoil (0.6–0.9 m) chemical (e.g. CEC, exch. Ca and Mg and ESP) properties. The **6ES** guidelines of Schroeder et al. (2009) were applicable to ameliorate topsoil ESP; the latter shown to influence yield percentage (Dennerley et al., 2018).

In the **Herbert** (see **Section 5.5**), a wavelet transform of the digital data (i.e. EM and γ-ray data) was used to enable prediction of topsoil (0-0.3 m) ESP. The DSM, using all the wavelet transformed digital data (i.e. elevation, EM and γ-ray data) gave the most accurate predictions. The **6ES guidelines** of Schroeder et al. (2006) to manage ESP through variable rates of gypsum was also demonstrated (Li et al., 2021a).

In the **Herbert** (see **Section 5.6**), a DSM approach was again used to identify zones by clustering digital data (i.e. EM and γ-ray data). The DSM was more accurate in predicting topsoil (0-0.3 m) and subsoil (0.6–0.9 m) chemical (e.g. CEC, exch. Ca and Mg) properties than a traditional texture map or field delineations. The **6ES guidelines** of Schroeder et al. (2009) were applicable for these properties (Arshad et al., 2019).

In the **Burdekin** (see **Section 5.7**), a DSM approach was used to predict topsoil (0-0.3 m) exch. Ca and Mg. The DSM was more accurate than a traditional map (Li et al., 2019a) and useful for applying lime and magnesium, respectively, using **6ES guidelines** (Schroeder et al., 2009). In terms of calibration, 30 samples were enough to predict exch. Ca with 40 for exch. Mg (Li et al., 2019b).

In **Proserpine** (see **Section 5.8**), a DSM was developed to predict topsoil (0-0.3 m) ESP. A map generated using ordinary kriging of 120 soil samples was satisfactory, but, a minimum of 100 samples was required. When digital data was used to value add to soil data, Cubist-RK outperformed OK with only 60 samples required. The **6ES guidelines** of Schroeder et al. (2009) were applicable to ameliorate topsoil ESP (Li et al., 2021b).

In **Proserpine** (see **Section 5.9**), a DSM was developed to predict topsoil (0-0.3 m) and subsoil (0.9-1.2 m) CEC. Topsoil prediction required 80 calibration samples whereas for subsoil only 30 were needed. Using both digital gave best results although γ-ray used alone slightly better than EM. Small transect spacing (i.e. 5 m) was recommended for topsoil, but larger spacing OK for subsoil (i.e. 5 – 60 m). The **6ES guidelines** of Proserpine (Calcino et al., 2010) were applicable to ameliorate topsoil CEC (Zhao et al., 2020).

Given the results presented in this Final Report and the published research, it can be concluded that the DSM approach can be applied to map various topsoil and subsoil physical (e.g. clay, silt and sand) and chemical (i.e. CEC, Exch. Ca, Exch. Mg and ESP) properties at the field and multi-field scale in different sugarcane growing districts. The final DSM can be used to apply the **6ES nutrient and ameliorant guidelines** in the four sugarcane growing areas investigated and including Mossman, Herbert, Burdekin, and Proserpine.

In terms of operational aspects, the following key conclusions can be made;

i) Various soil physical (e.g. clay, silt and sand) and chemical (i.e. CEC, Exch. Ca, Exch. Mg and ESP) properties can be mapped using a DSM approach, but regardless of modelling technique, the number of soil samples required to make a calibration was approximately the same (i.e. 1 sample per hectare) regardless of the soil property (i.e. topsoil Exch. Ca and Mg and ESP) or study area.

ii) Mathematical methods such as LMM are useful when digital data are correlated with soil data, with hybrid methods of machine learning (i.e. Cubist) and regression kriging (Cubist-RK) useful when correlations were statistically significant but not as strong and if residuals were spatially auto-correlated. Alternatively, wavelet analysis can also be useful to predict soil properties (i.e. topsoil ESP) where there was no direct relationship with digital data but a relationship with scale specific variation in digital data (i.e. γ-ray, EM and DEM). Moreover, fuzzy k-means or k-means clustering can be used to make management zones from γ-ray and EM data when the digital data is not directly correlated to the soil data of interest and produce superior predictions than traditional soil texture maps and or using field delineations to predict soil properties.

iii) Digital data of elevation, γ-ray and EM were best used in combination rather than alone, regardless of which modelling technique was considered (e.g. LMM, Cubist-RK and wavelet analysis). In terms of the density of digital data transect spacing, the smaller the spacing the better (i.e. transect every 7.5 m) with a maximum transect spacing of 30 m allowing large areas to be measured in a day (~ 400 ha).

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2. Background

2.1 Introduction

The Australian sugarcane industry operates in alluvial-estuarine areas of north-Queensland, which are characterised by sodic and infertile sandy soil. Therefore, from a production perspective there is a need to ameliorate (e.g. gypsum application) and fertilise (e.g. lime) the soil, respectively.

In terms of topsoil sodicity failure to ameliorate renders the soil susceptible to water erosion from intense rainfall events and as a function of poor soil structural stability. Lack of fertilisation can lead to losses in productivity and a decline in soil health as organic matter production is diminished.

Moreover, 70 % of sugarcane industry operates next to the Great Barrier Reef, and because of this cane farmers are under increasing pressures to improve practices to minimise off-farm pollution from erosion and movement of nutrient rich soil particles.

Farmers therefore need to know soil variation to enable them to apply fertilisers and ameliorates efficiently and effectively, which will result in improved soil condition and productivity and reduced runoff.

2.2 Six-easy-steps

Best-practice amelioration and fertilisation, according to the **Six-easy-steps (6ES)**, requires knowledge of soil variation to maximise yield and minimise losses, however. In sugarcane this requires information on soil nutrient (i.e. N, P, K and S) status (Sundara et al., 2002) as well as soil physical (e.g. clay, silt and sand) and chemical (e.g. pH, salinity, organic matter) properties. In addition, cation exchange capacity [CEC]) and exchangeable cations (i.e. Ca, Mg, Na and K) is also required.

There are many and varied reasons why this information is necessary. For example, knowledge about N is required because it drives biomass production, whilst P is needed because it promotes root growth and stimulates tillering. Moreover, clay content dictates soils potential to be leached of labile N, while chemical information such as pH indicates range of nutrients that may be available for uptake.

Similarly, exchangeable Ca and Mg are essential, the former because of the large amount of vegetative growth which requires structural rigidity and the later as the central element in chlorophyll which not only drives photosynthesis but sugar production.

So how can a cane farmer manage and account for the variation of so many soil physical and chemical properties when sampling and laboratory analysis is expensive and time consuming? For example, if a single topsoil sample were to be analysed for the myriad of soil physical and chemical properties, it would cost up to A$125 per sample to analyse. Moreover, additional samples are required across the field and at multiple depths to ascertain if subsoil properties constrain yield.

2.3 Digital Soil Mapping (DSM)

One approach is to use Digital Soil Mapping (DSM). This is because cheap-to-acquire digital data is used in conjunction with statistical methods to map individual soil properties. At the field scale, it is popular to use proximal sensing electromagnetic (EM) induction instruments because they measure the soil apparent electrical conductivity (EC_a - mS/m), which is often directly correlated with properties relevant to agricultural productivity, including clay, CEC, salinity and moisture.

For example, DSM of clay have been created from correlations with EC_a (Huang et al., 2014a), with the information indicating where water logging or deep drainage can be problematic (Woodforth et al., 2012). The DSM approach can also potentially be applied to monitor N leaching and runoff across canegrowing (Verburg et al., 1998) and minimising these losses will improve yield and reduce the chance of adverse effects on the GBR. Similarly, DSM of CEC (Triantafilis et al., 2009a) and the exchangeable sodium percentage (Huang et al., 2014b) using EM data provided information about soil fertility and structural resilience, respectively and where to mitigate salinity (Triantafilis et al., 2001). Mapping these soil properties is crucial in sugarcane because fertility, sodicity and salinity greatly control yield (Wiegand et al., 1996).

In recent research, carried out by UNSW, and in collaboration with HCPSL, as part of a Reef Rescue Project, it has been shown that the three particle size fractions (PSFs) of clay, silt, and sand, have been mapped using DSM methods. This was achieved using a DUALEM-421, RS700 γ-ray spectrometer and elevation data. The implications for this is that the study field was located on the SRA site (Ingham). Specifically, the spatial variation can now be considered in setting-up and interpreting trial results using mixed-models and thereby determine which varieties are most suited to given soil textures and soil type (Muzzamal et al., 2018).

In circumstances where direct correlation between soil properties and ECa do not exist, or where multiple properties need to be managed, EC_a has been used to identify zones. This was the case in a potato field in St. Amable Quebec, Canada, where Cambouris et al. (2006) clustered EM38 EC_a to identify management zones that accounted for variation in soil moisture. Triantafilis et al. (2009b) extended this idea by clustering EM38 and EM31 EC_a data along with red, green and blue data to identify management zones, which differed in soil properties (i.e. clay, CEC, EC_e) relevant to gypsum requirement. More recently, Bramley et al. (2011) used clustering to define zones based on infrared and red reflectance from a remotely-sensed image, yield maps and EM38 EC_a, finding the sensory and chemical analysis of wine made from fruit from each zone was statistically different as were soil properties (e.g. CEC).

While the popularity of EM data in DSM is evident, increasingly γ-ray data is being used in concert with EM to identify soil management zones (Altdorff & Dietrich, 2012). This is because γ-ray data provides information about soil parent material as well as mineralogical and chemical properties (Triantafilis et al., 2013). In terms of identifying management zones, Huang et al., (2014c) showed how clustering of EM38 and γ-ray could be used to identify soil types that were related to geology in Nottinghamshire, UK. More significantly the approach identified statistically different zones based on topsoil (0-0.10m) physical (i.e. clay) and chemical (i.e. pH) properties; with the results applicable to prescribing lime application rate and as a function of differences in soil acidity.

In a much larger setting, Zare et al. (2016) showed that ground based EM38 and remote sensed (airborne) γ-ray data could be used to identify management zones across 25,000 hectares of a highly productive and predominantly alluvial clay plain near Bourke, NSW. Similar zones were determined across a larger (40,000 ha) and more physiographically diverse landscape near Gunnedah, NSW (Jing et al., 2017). In both cases, a larger suite of soil physical (i.e. clay, silt and sand) and chemical (i.e. pH, EC_e, CEC, exchangeable Ca, Mg, Na and K, ESP) properties were shown to be statistically different. The results were therefore applicable in terms of how the soil types identified in each zone could be managed as a function of the interrelationships between the different soil properties.

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3. Objectives

The aim of this project was to determine whether **digital data**, including proximal sensed **EM** data acquired from a DUALEM-421 and γ-ray data from an RS700 γ-ray spectrometer can be used with **mathematical methods** to create **digital soil map (DSM)** of either

i) individual soil physical (e.g. clay) or chemical (e.g. CEC, ESP, exch. cations) properties, or
ii) identify soil management zones,

to ameliorate (e.g. gypsum application) and/or fertilise (e.g. lime) soil condition and thereby manage soil variability across sugarcane fields in various areas of far north Queensland. In some instances, comparisons of the **DSM** were made with traditional soil maps and using other sources of digital data such as elevation and yield (2014, 2015 and 2016) where these were available.

In its simplest terms, this project will provide a **DSM** methodology to map either soil properties individually or identify soil management zone which will allow cane farmers and consultants to identify "causal" factors of below ground soil variation which "effects" yield.

In doing so, cane growers and consultants will be provided with **case studies in four sugarcane** growing areas, including;

i) **Herbert**,
ii) **Mossman**,
iii) **Proserpine**, and
iv) **Burdekin**,

where managing soil variability is possible with the **6ES nutrient and ameliorant management guidelines**, and which leads to improving crop yield from year-on-year monitoring and as an "affect" of the efficient and strategic addition of ameliorants and fertilisers. After all "Seeing is believing."

4. Methods

4.1 Digital data

Two different sources of digital data were acquired, including from a γ-ray spectrometer, and an EM induction instrument data which measures the soil apparent electrical conductivity (EC_a – mS m^{-1}).

The γ-ray spectrometry data was obtained from a Radiation Solutions RS-700 (Radiation Solutions, Mississauga, Ontario, Canada) instrument (see **Figure 1a**). The γ-rays are detected by a Radiation Solutions crystal pack (RSX-1), which was mounted on a bracket at the front of a 4WD vehicle. The crystal pack, which is coated with NaI, measures the γ-ray being emitted from various radioelements from energy windows (Erdi-Krausz et al., 2003) of;

i) potassium (**K**: 1.37 – 1.57 MeV),
ii) uranium (**U**: 1.66 – 1.86 MeV),
iii) thorium (**Th**: 2.41 – 2.81 MeV), and
iv) across whole spectrum, that is the Total Count (**TC**: 0.41 – 2.81 MeV).

The measurement of various elements is converted as follows; **K** in percentage (%), with **U** and **Th** measured in parts per million (ppm) and **TC** in counts per second (cps).

Figure 1a: Radiation Solutions RS-700 (Radiation Solutions, Mississauga, Ontario, Canada) and RSX-1 detector.

Figure 1b: DUALEM-421 electromagnetic (**E**M) induction instrument (Mississauga, Ontario, Canada).

The EM data was collected from a DUALEM-421 instrument (Mississauga, Ontario, Canada). Briefly, the instrument (see **Figure 1b**) has a transmitter coil located at one end of the instrument. To avoid interference with the vehicle, it was usually situated far enough away from the vehicle so that the effect of it could not be detected.

It also includes a series of horizontal co-planar (HCP) and perpendicular (PRP) receiver array pairs. The distance between the transmitter to the HCP receivers are 1, 2 and 4 m. Given the instrument operates at a low frequency (9 kHz), the coil spacings give a theoretical depth of EC_a of 0 – 1.5 m (1mHcon), 0 – 3.0 m (2mHcon) and 0 – 6.0 m (4mHcon), respectively. The distance between the transmitter and PRP coils are 1.1, 2.1 and 4.1 m, which gives theoretical EC_a of 0 – 0.6 m (1mPcon), 0 – 1.2 m (2mPcon) and 0 – 2.4 m (4mPcon), respectively.

Digital Elevation Model (DEM) and yield percentage data were also used and where available in a particular area. This was mainly the case only in the Herbert and with the kind assistance and support of Messrs Lawrence Di Bella, Michael Sefton and Rod Nielson.

4.2 Soil data

Soil samples were collected on approximately 50 x 50 m grids and taken from various depth increments and for the most part from the topsoil (0-0.3 m), subsurface (0.3-0.6 m), subsoil (0.6-0.9 m) and deeper subsoil (0.9 -1.2 m).

Various soil physical (i.e. clay, silt and sand) and chemical (e.g. cation exchange capacity, exchangeable cations [Ca, Mg, Na K], soil organic carbon [SOC], pH, $EC_{1:5}$), properties were investigated with laboratory data generated using the following methods.

Particle size fraction (clay, silt, and sand): All the samples were air-dried, crushed, and passed through a 2 mm sieve before measurement. The samples were analysed in the laboratory for soil particle size fractions (i.e. clay, silt, and sand content) according to the hydrometer method (Rayment and Higginson, 1992).

Cation Exchange Capacity (CEC): All the samples were air-dried, crushed, and passed through a 2 mm sieve. Tucker's method was used to determine the Cation Exchange Capacity (**CEC**) using a mechanical leaching device (Holmgren et al., 1977). Briefly, samples were first washed with 60% ethanol to remove any soluble salts. This was followed by extraction with 1 mol NH4Cl. The extracts were analysed using an inductively coupled plasma optical emission spectrometry (ICP-OES) (Olesik, 1991).

The concentration of exchangeable cations (i.e. exch. Calcium [Ca], magnesium [Mg], sodium [Na] and potassium [K]) were measured, and thereby the CEC (cmol(+)/kg) was determined by the sum of the cations. The exchangeable sodium percentage (ESP - %) was calculated using standard equation of ESP (%) = exchangeable [Na/Ca + Mg + Na + K] x 100).

Soil Organic Carbon: SOC was determined using the mass loss on ignition (LOI) method (Davies, 1974). Specifically, a known weight (1-3 g) of air-dry soil sample was added to a tared crucible, dried in the laboratory oven at 105 ^{o}C for 24 h, cool in a desiccator. A muffle furnace was preheated to 550 ^{o}C and soil was heated in the furnace at that temperature for 2 h, followed by being placed again in a desiccator to cool. The difference between the mass of the crucible and soil before and after heating was assumed to be the mass of SOM in the soil sample. SOC was then estimated by dividing SOM with a conversion factor of 1.72 (Rayment and Lyons, 2011).

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5. Case Studies

5.1 Mossman - Determination of optimal mathematical model, sample size, digital data and transect spacing to map CEC in a sugarcane field

(Note: Paper submitted to COMPAG and will be forwarded to SRA on publication)

Introduction

Nitrogen (**N**) is one of the main building blocks of plant proteins and is a necessary component in cell structure and function. It is essential for chlorophyll synthesis, particularly in sugarcane. Moreover, deficiency in **N** leads to reduced root mass and stalk population, which leads to lower crop yields. **N** fertilisation is important to maintain productivity. However, fertilization inconsistent with plant nutritional needs may increase the risk of environmental pollution (e.g. off-farm run-off or leaching).

To improve N management, the sugarcane industry developed the 6ES nutrient management guidelines (Schroeder et al., 2010), which consider N mineralised from soil organic carbon (SOC, %). This is because one source of available N is in-season mineralisation, where N comes from SOC breaking down into inorganic forms of N which becomes available to plants.

However, the **6ES guidelines** (**Table 5.1**) suggest varying N application rates for different levels of SOC. For example, to achieve a district yield potential of 120 t/ha after a bare fallow, a very low (< 0.4 %) SOC would require an application rate of 140 kg/ha, whereas a very high (> 2.4 %) SOC would require only 80 kg/ha. Thus, knowledge about the SOC is necessary to ensure efficient application of N to address infertility.

Table 5.1 N application guidelines for sugarcane after bare fallow on district yield potential of 120 tonnes of cane/ha and N mineralisation index in Mossman River Valley (Schroeder et al., 2010) based on soil organic carbon (SOC, %).

Soil nitrogen (N) mineralisation index	SOC (%)	N application rates (kg/ha)
Very Low	< 0.4	140
Low	0.4-0.8	130
Medium-Low	0.8-1.2	120
Medium	1.2-1.6	110
Medium-High	1.6-2.0	100
High	2.0-2.4	90
Very High	> 2.4	80

Aims: Herein we wanted to test components of DSM to predict topsoil (0-0.3 m) SOC (%) by comparing;

i) Various models (i.e. geostatistical (OK and RK), machine learning (random forest [RF] and support vector machine [SVM]), and hybrid (RF regression kriging [RFRK] and SVMRK),
ii) Suitable number of samples (10, 20, 30,…, 110) for calibration,
iii) Digital data including proximal (i.e. γ-ray and EM) and remote (i.e. Land Surface Temperature [LST – T °C]) used either alone or in combination, and
iv) Application of one size fits all with 6ES nutrient guidelines in terms of cost.

These comparisons are assessed using an independent validation (i.e. 23) data set and evaluated by Lin's concordance correlation coefficient (LCCC) and accuracy, using ratio of performance to deviation (RPD). We determine the N fertiliser requirement considering a district yield potential of 120 t/ha after a bare fallow and based on the 6ES nutrient guidelines for the Mossman Valley. A cursory comparison of the cost of application of N using the DSM method and a paradigmatic one-size fits all approach was also considered.

Study area

The study area (16.543° S, 145.474° E) is located approximately 17 km south-east of Mossman and south of Craiglea, Queensland, Australia. The study site includes three fields which cover a total area of 48 ha with a perimeter of 2,934 m. The soil includes Kandosols (KA) in the eastern half and Tenosols (TE) and/or Rudosols (RU) in the western half of the study area (**Figure 5.1.1a**). **Figure 5.1.2** shows digital data collected across the three study fields, including; **a)** γ-ray, **b-c)** EM, and **d)** LST.

Results

The most statistically significant digital data used in combination included proximal γ-ray (TC), EM (1mHcon and 2mHcon), and remote (i.e. LST) sensed data plus Northing. SVMRK performed best using all (i.e. 110) calibration data, producing moderate agreement (LCCC = 0.73) and fair (RPD = 1.65) accuracy. This was also the case when size was >= 50, but when < 50, RFRF gave equivalent agreement (0.70) and accuracy (1.55).

Similar results were achieved when only γ-ray (TC) was used, however, RFRK produced moderate agreement and fair accuracy using as few as 20 and as many as 70 samples, with the optimal being 40 (i.e. LCCC = 0.79 and RPD = 1.70). The latter amounts to 1 calibration sample being required per ha to enable calibration. By comparison, OK and RK produced poor agreement (<= 0.65) and accuracy (<= 1.4) regardless of sample size.

The final DSM of SOC created using RFRK provided an indication of soil condition that limits soil capability to store N as a function of SOC and acts a means to replenish soil capital with N application rates according to the 6ES. Specifically, Tenosols and Rudosols require 130 kg/ha to 120 kg/ha, whereas Kandosols require 110 kg/ha. The DSM equates to a potential ~ 22 % decrease in the cost of N fertilizer application, compared to a one-size fits all approach.

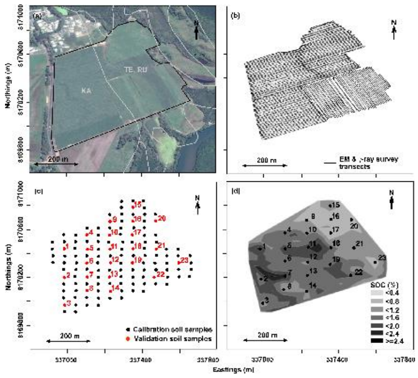

Figure 5.1.1a) Soil Orders, **b)** digital data transects, **c)** soil sampling sites and **d)** topsoil (0-0.3 m) SOC (%).

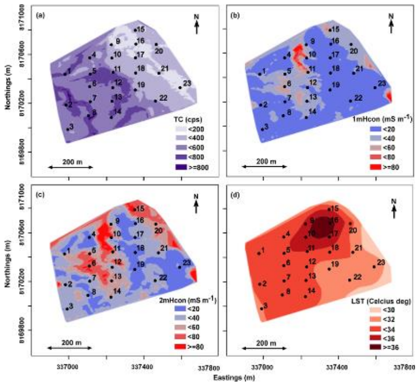

Figure 5.1.2a) γ-ray of TC; and, EM including **b)** 1mHcon, and **c)** 2mHcon; and, **d)** remote LST.

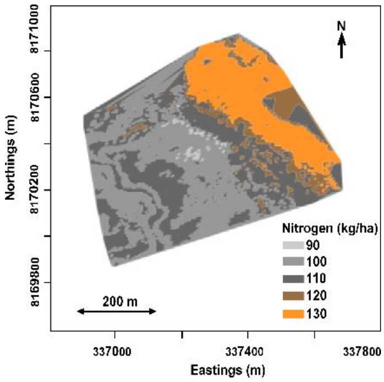

Figure 5.1.3 DSM of N (kg/ha) for sugarcane yield of 120 t/ha post fallow using topsoil SOC (%).

Conclusions

Figure 5.1.3 shows the N rate (kg/ha) required after bare fallow and based on DSM of topsoil (0-0.3 m) SOC and using **6ES guidelines** (**Table 5.1**). Large (130 kg/ha) and intermediate-large (120 kg/ha) N is required in the eastern third, characterised by low (0.4-0.8 %) and medium-low (0.8-1.2 %) **SOC**, respectively. Conversely, intermediate-small (100 kg/ha) and small (90 kg/ha) N is required in centre and western third, associated with a drainage channel, characterised by medium-high (1.6-2.0 %) and high (2.0-2.4 %) SOC, respectively.

Herein, the DSM provides an indication of soil condition which limits soil capability to store N as a function of SOC. The DSM of SOC acts a means to replenish the soil capital with N application rates according to the 6ES guidelines. It is estimated that 5,244 kg of N would be needed to be added and using precision applicators to match N requirement. This would equate to a total cost of A$7,185.

In terms of achieving a district yield potential of 120 tonnes of sugarcane/ha using a uniform N application rate of 140 kg/ha for plant sugarcane after a bare fallow, this would require the application of 6,720 kg of N. This amounts to a total cost of A$9,206. The use of DSM equates to a potential of ~ 22 % decrease in the cost of N fertilizer application.

References

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5.2 Mossman - Proximal sensed digital library to predict topsoil (0-0.3 m) clay across multiple sugarcane fields: Applicability of local and universal support vector machines

(See **Appendix 5.2_2021_Arshad_CATENA_Clay-CEC_library**)

Introduction

The fate and transport of nutrients is affected by the existing situation of soil physicochemical properties. For instance, the small size (< 2 μm), large surface area and overall negative surface charge of clay particles enable storage of water and retention of nutrient. Soil high in clay (> 35%) is as difficult to manage as soil with less clay (< 15%) as the former tends to waterlog and locks nutrients. Knowledge of topsoil (0 – 0.3 m) clay is important because it acts as interface between nutrients and sugarcane ratoons.

In sugarcane areas, laboratory data have been modelled with digital data using linear regression and linear mixed models (LMM). While good for individual fields, locally, these site-specific linear models might be unable to handle the non-unique nature of digital data (i.e. γ-ray and EM) across multiple locations. To overcome this, machine learning (ML) methods (e.g. support vector machine - SVM) can be used as they can handle non-linear relationships, outliers, small datasets, and overfitting.

Aims: Herein we wanted to test components of DSM to predict topsoil (0-0.3 m) clay (%) comparing;

i) Various sources of digital data (i.e. combined or individual)
ii) Local SVM using site-specific with universal SVM in site-independent, holdout and spiking,
iii) Number of samples for spiking, and
iv) Final DSM in Mossman of each method and in terms of uncertainty of prediction.

These comparisons are assessed using an independent validation (i.e. 30 %) data set and evaluated by Lin's concordance correlation coefficient (LCCC) and accuracy, using ratio of performance to deviation (RPD).

Study area

Soil and digital data was collected from six study sites situated in Queensland, Australia, from **Proserpine** (20° 19'7"S, 148° 29'24"E), **Burdekin** (19° 41'0"S, 147° 12'9"E), **Herbert** valley including Helen's Hill South (18° 48′55″S, 146° 6'35"E), Helen's Hill (18° 46'49"S, 146° 9'58"E) and Ingham (18° 39'32"S, 146° 8'10"E) and **Mossman** (16° 32'39"S, 145° 28'28"E). The size of these study sites varied from a small field in Helen's Hill (5.00 ha) and Ingham (7.55 ha) to intermediate sites in the Burdekin River Valley (32 ha), Helen's Hill South (35 ha) and Mossman (38 ha) to the largest site in Proserpine (70 ha).

Results

Figure 5.2.1a) shows the DSM of topsoil clay (%) in Mossman and using site-specific approach; whereby a calibration was established at each site independent of the others. It shows a boundary between two soil types (i.e. Kandosol and Rudosol) was well resolved. Moreover, the prediction of large clay (> 40 %) was discerned along western margin and in a narrow band, which defines location of a prior stream channel.

Figure 5.2.2a) shows overall that the Lin's (0.92) and RPD (2.60) showed excellent agreement (> 0.90) and accuracy (> 2.5), respectively. This was typified by predictions in Mossman, which were close to 1:1 line. There were outliers, for example, clay (%) was under-predicted at some locations of Proserpine. Nevertheless, uncertainty could be mapped and as shown **Figure 5.2.3a)**, indicated that in the west there was a small confidence interval (CI < 4), whereas the clayey east it was intermediate-small CI (4 – 5).

Figure 5.2.1b) shows the DSM of topsoil **clay** (%) in Mossman and using site-independent approach. **Figure 5.2.2b)** shows that combined validations for universal SVM and in site-independent approach were comparable, yet, slightly smaller than that of site-specific results. Specifically, Lin's (0.88) showed strong agreement (Lin's > 0.80) with RPD (2.17) with very good accuracy (RPD = 2.0 – 2.5).

As with the site-specific approach, the same outliers were problematic, however, a growing number of sites were also under-predicted in Mossman. While the broad patterns of soil type were evident, **Figure 5.2.3b)** shows uncertainty (CI) was intermediate-large (6 – 7) to large (> 7) at the boundary.

Figure 5.2.1c) shows the holdout approach to DSM; whereby sites being predicted were not included in the calibration. **Figure 5.2.2c)** shows the combined validations did not bring improvement in performance of SVM for holdout areas with overall agreement (Lin's = 0.55) and accuracy poor (RPD = 1.2). This was evident in the uncertainty map (**Figure 5.2.3c)** that indicated intermediate-large CI (6 – 7) for most parts in the east.

Figure 5.2.1d) shows that spiking improved the performance of the SVM for holdout areas with results (Lin's = 0.91, RPD = 2.51) equivalent to that of site-specific validations (**Figure 5.2.2d)**. There were outliers, however, exemplified again in Mossman where a prior stream channel was evident. Nevertheless, CI (**Figure 5.2.3d**) was equivalent to site-specific approach where it was intermediate-small (4 – 5) or small (< 4).

Figure 5.2.2 shows overall, the predictions showed that excellent accuracy was achieved using site-specific (2.60) and spiking (2.51). This was especially the case for study sites with large clay (%), high data variability (i.e. CV) and or good R^2 with digital data (i.e. **Burdekin**, **Mossman**, **Proserpine**).

In terms of amount of calibration and spiking data the results were equivocal. Where the accuracy was excellent, good, and fair, the size of calibration data set did not greatly influence prediction. However, the change in spiking set did influence accuracy and generally diminished when the set was only 20 or 10 % of the data available.

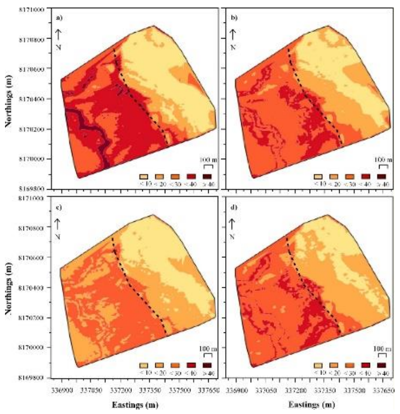


Figure 5.2.1 DSM of topsoil **clay** (%) in Mossman using **a)** site-specific, **b)** site-independent, **c)** holdout, and **d)** spiking.

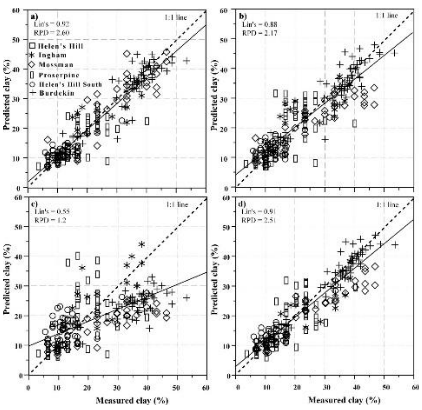


Figure 5.2.2 Measured v predicted topsoil **clay** (%) for all six study sites using **a)** site-specific, **b)** site-independent, **c)** holdout, and **d)** spiking.

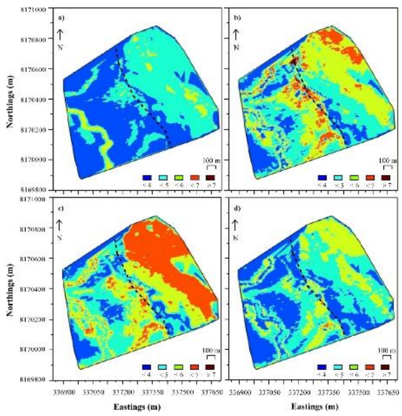


Figure 5.2.3 Uncertainty for topsoil clay (%) in Mossman, showing 90% CI of **a) site-specific, b)** site-independent, **c)** holdout, and **d)** spiking.

Conclusions

It is best to develop digital data libraries to be site-specific, but site-independent and spiking approach give almost as good prediction agreement and accuracy. We recommend future work should be undertaken with the inclusion of other sources of digital data (e.g. elevation and yield) to improve SVM model development.

Moreover, additional digital and soil data could be taken in adjacent fields for sites like Helen's Hill South where poor predictions were attributable to small mean clay (%) and less variability (i.e. CV). Additional data is also likely to improve the predictions for smaller study sites like Helen's Hill (5 ha) and Ingham (7.55 ha) where there were much smaller calibration and spiking sample sizes.

The models used herein can be extrapolated to map deeper depths. This will be particularly beneficial to ascertain the subsoil yield constraints, particularly in the duplex soil profiles. Moreover, the models should be used in adjacent fields and farms from those studied to see if they can be used to make DSM and without the need for recalibration and therefore collections of new soil samples.

Finally, the approach should also be used to see if other soil physical (i.e. sand and silt) or chemical (e.g. CEC, exch. Ca and Mg, pH) can be developed into calibration models with digital data and using SVM.

5.3 Herbert - Mapping topsoil and subsoil cation exchange capacity (CEC) using Bayesian modeling and proximal sensors at the field scale

(see **Appendix 5.3_2021_Arshad_CATENA_Clay-CEC_library**)

Introduction

The CEC is needed because it is a measure of binding of exchangeable cations (i.e., Ca^{2+}, Mg^{2+}, Na^{+}, and K^{+}). The CEC also reflects fertility, acidity, structure, and affects ability of soil to store and filter chemicals as well as buffer pH from changes. This is particularly the case in the sugarcane growing areas because the soil is sandy (> 60 %), strongly acidic (pH < 5.5) and often strongly sodic (ESP > 15 %).

For these reasons, sugarcane farmers need to take samples so that appropriate fertiliser (e.g. liming) rates can be determined. In the Herbert valley, this is done according to the **6ES nutrient management guidelines** (SRA, 2013); with the application of either a small (2.25 t/ha) amount of lime when CEC is low (i.e., <3 cmol(+)kg^{-1}), an intermediate amount (4 t/ha) when CEC is medium (3–6 cmol(+)kg^{-1}), or, large (5 t/ha) when CEC is high (>6 cmol(+)kg^{-1}). Unfortunately, obtaining this information is time-consuming and expensive.

Aims

The primary aims of this study was to use a DSM approach to map,

i) Topsoil (0–0.3 m) and subsoil (0.6–0.9 m) **CEC** and estimate their posterior distributions using and evaluating the uncertainty using a Bayesian inference approach (Integrated Nested Laplace Approximation with Stochastic Partial Differential Equation - INLA-SPDE), and
ii) Compare the model performance of INLA-SPDE with regard to different digital data (elevation, γ-ray spectrometry and EM) by taking digital data as uncertain (measured with error) and accounting for this error in the estimation of the model parameters.

The performance of the models fitted in this study was validated using a leave-one-out cross-validation using measures of prediction accuracy (root mean square error), bias (mean error), agreement considering concordance (Lin's), and credibility intervals estimated by INLA-SPDE. Topsoil and subsoil maps of credibility interval (CI) indicate where improvements in **CEC** prediction can be achieved were investigated.

Study area

The study field is located near Helen's Hill approximately 13 km south of Ingham (146°16'E, 18°78'S) in the Herbert River Valley, Queensland, Australia. The field is about 5 ha, with dimensions approximately 280 m long and 200 m wide. The sugarcane is grown in east-west aligned beds which are orientated down a gentle slope. The yield varies systematically, with the western part higher yielding year-on-year.

Results

Figure 5.3.1a shows the measured topsoil CEC and **Figure 5.3.1b** subsoil CEC. The patterns were similar, but the trend showed subsoil CEC was smallest in the southwest and centre of the field, rapidly increasing in the northeast (>8 cmol(+)kg^{-1}) approximately two-thirds of the way across the field.

Figure 5.3.1b shows the spatial distribution of the γ-ray data of **K** (%). The centre and southwest were characterized by small **K** (<1.5 %), whereas the north-western and north-eastern were large (>4.5 %). The north central part was intermediate-large (3.5–4.5 %) and south-east intermediate-small (2.5–3.5 %).

The spatial distribution of elevation was highest (>9.5 m) in the west (not shown), decreasing gradually to the east where it was lowest (<8 m). The EM data was generally in agreement with the spatial distribution of the γ-ray spectrometry data (not shown).

Figure 5.3.2a shows the DSM (using all digital data) of predicted topsoil CEC was large (>8 cmol(+)kg^{-1}) along the eastern margin. Otherwise, topsoil CEC was generally small (<2 cmol(+)kg^{-1}) in the southwest and centre and increased to intermediate-small (2–4 cmol(+)kg^{-1}). To appreciate the digital data used, **Figure 5.3.2b** shows the 95% CI, here, which was delineated by the difference between 2.5% and 97.5% percentiles.

Figure 5.3.2b shows the most credible predictions were in the southeast and centre where CI was small (<2 cmol(+)kg^{-1}). As with measured **CEC**, the CI increased in a northeast direction, whereby CI was large along the eastern margin (>8 cmol(+)kg^{-1}). We attribute this to edge effect of EM data, which occurs at the boundary; where the underlying soil moisture led to an increase in EM.

Figure 5.3.2c shows predicted subsoil **CEC**, with similarities with measured subsoil **CEC**. The difference was that the transition between the area of small (<2 cmol(+)kg^{-1}) and large subsoil (>8 cmol(+)kg^{-1}) **CEC** occurs over a very short spatial scale.

Figure 5.3.2d shows the 95% CI for subsoil **CEC**. Again, the most credible predictions were in the southeast and centre where CI was small (<2 cmol(+)kg^{-1}). However, while the CI again increased in a northwest direction, the change to large CI occurred approximately 2/3rds of the way across the field. This was attributed to edge effects and was most obvious where there was a marked a change in the digital data.

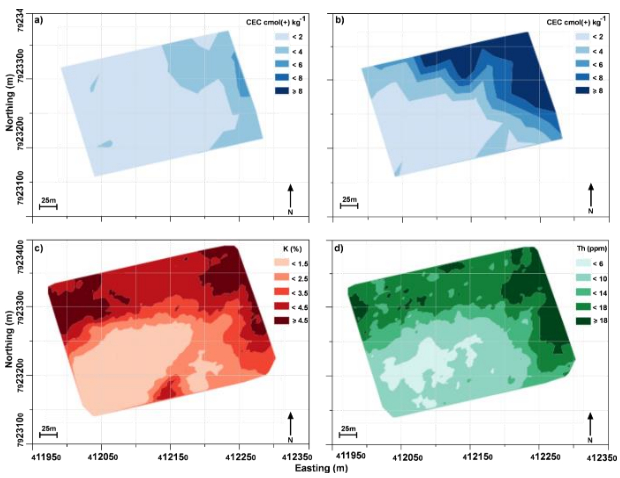


Figure 5.3.1: Contour plot of measured CEC (cmol(+)kg^{-1}) for **a)** topsoil (0–0.3 m), and **b)** subsoil (0.6–0.9 m) and γ-ray spectrometry **c)** K (%), and **d)** Th (ppm).

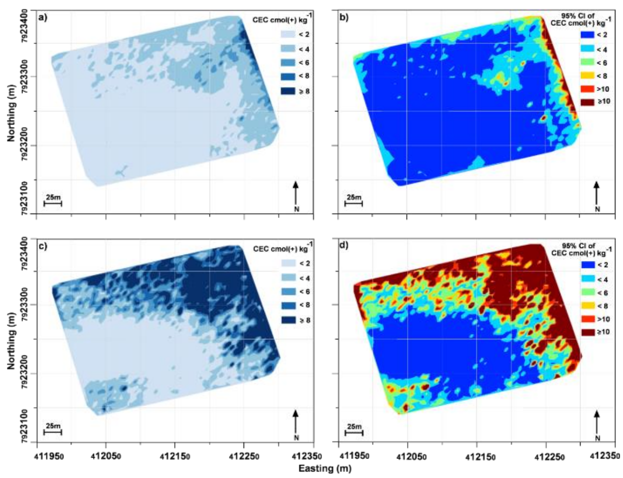


Figure 5.3.2: DSM of CEC (cmol(+)kg^{-1}) by INLA-SPDE for **a)** topsoil (0–0.3 m), and **c)** subsoil (0.6–0.9 m) and 95% credibility intervals (CI) for **b)** topsoil, and **d)** subsoil.

Conclusions

It was also noted that the ground-based γ-ray spectrometry data had a higher signal-to-noise ratio compared with the ground-based EM data, but a lower signal-to-noise ratio compared with the RTK GPS data. These results were reflected in the maps of the credibility interval (CI), where better CEC predictions were achieved in the topsoil compared to the subsoil.

We also conclude that using various digital data sources in combination was most accurate to predict **CEC**, least biased and had the highest concordance in both the topsoil and subsoil than using the digital data alone.

In this study, the best set of digital data, when used alone, and for DSM CEC in the topsoil was γ-ray spectrometry, followed by EM data and elevation. For subsoil CEC, it was elevation, followed by γ-ray and EM data. In terms of improving prediction, additional information is required in areas where soil texture and underlying change in geology occurs about 2/3rds of the way down the slope and on the margins of the field where edge effects caused under- and over-prediction problems.

Nevertheless, the final DSM of topsoil CEC allows for the application of the **6ES nutrient management guidelines** (Sugar Research Australia, 2013) with the application of either small (2.25 t/ha) amounts of lime when **CEC** was low (i.e., <3 cmol(+)kg^{-1}), or conversely large (5 t/ha) amounts when CEC was high (>6 cmol(+)kg^{-1}). Unfortunately, obtaining this information is time-consuming and expensive.

References

Sugar Research Australia (2013). Six easy steps nutrient management guidelines for sugarcane in the Herbert district. Sugar Research Australia, Indooroopilly QLD, Australia.

5.4 Herbert - Identifying soil management zones in a sugarcane field using proximal sensed electromagnetic induction and gamma-ray spectrometry data

(See **Appendix 5.4_2018_Dennerley_SUM_Zones**)

Introduction

The Australian sugarcane industry operates in alluvial-estuarine areas of Queensland, which are characterised by sodic and infertile sandy soil. There is a need to ameliorate and fertilise the soil. Best-practice amelioration and fertilisation require knowledge of variation to maximise yield and minimise loss. Information about soil physical (e.g. clay) and chemical (e.g. pH, CEC) properties are necessary because they determine ameliorant and nutrient availability, respectively.

Aims: The aim of this study is to determine whether;

i) Digital data, including EM and γ-ray data could be clustered to identify soil management zones across a sugarcane field, and
ii) Compare the results by clustering the percent yield variation in sugarcane collected over three successive years (2014, 2015 and 2016).

To test the zones derived from digital and yield data, we use restricted maximum likelihood analysis (REML) of various topsoil (0–0.3 m) and subsoil (0.6–0.9 m) physical (e.g. clay) and chemical (e.g. pH, CEC, exch. Ca and Mg) properties of zones. To provide a practical demonstration of soil use and management, we determine gypsum requirement to ameliorate sodic conditions and fertiliser requirement in terms of calcium (lime) and magnesium (Mg). These were made with respect to **6ES** guidelines (Schroeder et al., 2009).

Study area

The study field is located at 'Orient' and is ~3 km east of Helens Hill (150°21' E, 31°06' S) in the Herbert River Valley, Queensland, Australia. The field is ~280m long and 200m wide and ~5ha in area.

Results

Figure 5.4.1 shows the maps of the study field including **a)** air-photograph, **b)** EM and γ-ray spectrometry survey transects and **c)** soil sample locations, and **d)** elevation (m) across the study field. **Figure 5.4.2** shows the EM **a**) 1mPcon, **b)** 2mPcon, and γ-ray spectrometry data; **c)** thorium (Th – ppm) and **d)** total counts (TC – cps).

Figure 5.4.3 shows the maps of management zones, with **Figure 5.3.1b)** showing 3 zones. Given the wide cross-section of physical and chemical properties minimised for 3 zones, in the topsoil and subsoil, it was worth determining how the zones performed considering using only percent yield variation. The DSM achieved using this digital data is shown in **Figure 5.4.3c).**

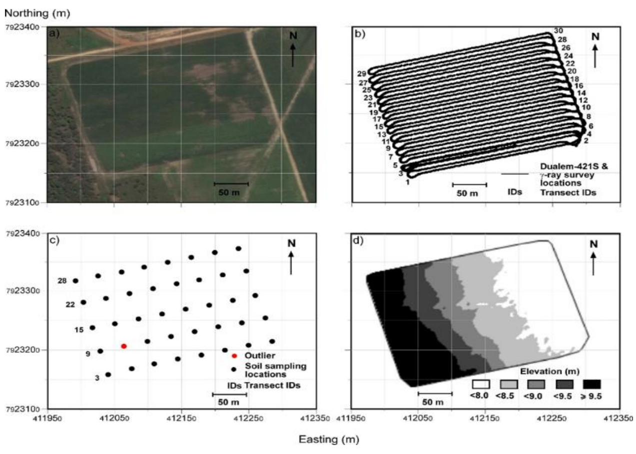


Figure 5.4.1: Study field **a)** air-photograph, **b)** EM and γ-ray spectrometry survey transects and **c)** soil sample locations, and **d)** elevation (m) across the study field.

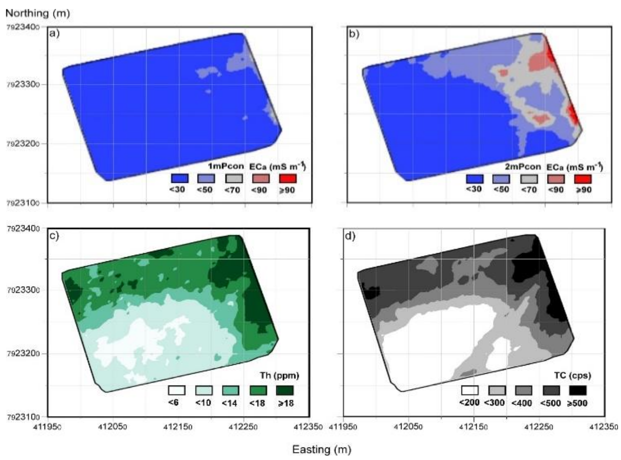


Figure 5.4.2: Spatial distributions of EM including; **a**) 1mPcon, **b)** 2mPcon, and γ-ray spectrometry data; **c)** thorium (**Th** – ppm) and **d)** total counts (**TC** – cps).

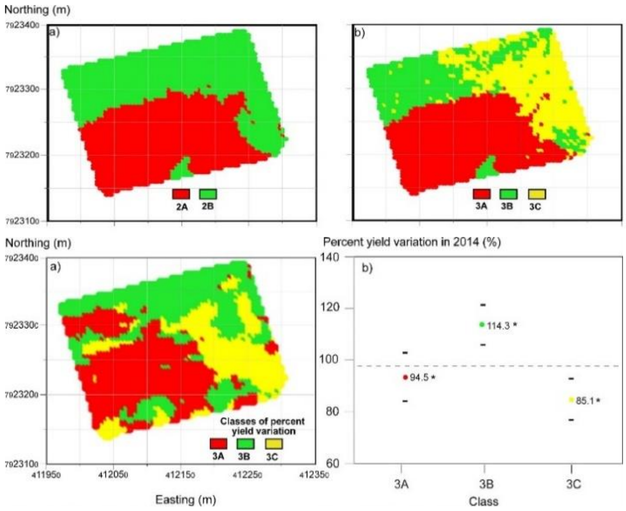


Figure 5.4.3: DSM of zones from **EM** and γ-ray data, including; **a)** 2, and **b)** 3, zones, and zones from **c)** yield data over 3 years (i.e. 2014, 2015, 2016) and **d)** percent yield variation for 2014.

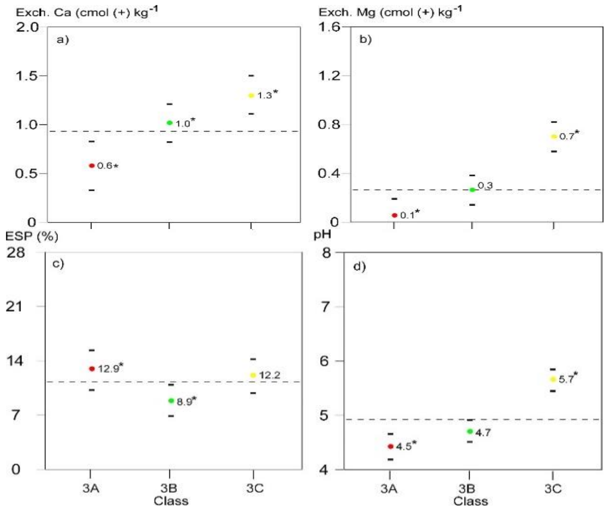


Figure 5.4.4: Mean and SD of topsoil (0-0.3 m) **a)** clay, **b)** CEC, **c)** ESP (%), and **d)** pH for 3 management zones derived from EM and γ-ray data.

Figure 5.4.3 shows the mean and standard error of topsoil (0–0.3 m) exch. cations from the REML estimated LMM and considering 3 zones (**Figure 5.4.3b**). **Figure 5.4.4a)** shows exch. Ca was statistically different for 3A (0.6 cmol(+)/kg), 3B (1.0 cmol(+)/kg) and 3C (1.3 cmol(+)/kg). According to the **6ES guidelines for nutrient management** in the Herbert, these levels require addition of lime in the order of 3, 2 and 1.5t/h, respectively.

Figure 5.4.4b shows topsoil exch. Mg was statistically different, but only for 3A (0.1 cmol(+)/kg) and 3C (0.7 cmol(+)/kg), with 3B (0.3 cmol(+)/kg) not statistically different. At these levels, the **6ES** guidelines suggest for zone 3A to have 125 kg/ha of Mg fertiliser applied, while no Mg fertilisation is necessary for 3B and 3C.

With respect to topsoil ESP (**Figure 5.4.4c**), zone 3C (12.2 %) was not statistically different from either 3A (12.9 %) or 3B (8.9 %), which were different from each other. According to the **6ES** for ameliorant management, these levels require addition of gypsum for the strongly sodic (10–15 %) 3A (12.0 %) and 3C (12.2 %) of 4t/ha, whereas the moderately sodic (6–10 %) zone 3B only requires 2t/ha. The results were consistent with percentage yield variance, suggesting the lower yield (e.g. 2014) in some zones (see Figure**5.4.3d**) is due to topsoil sodicity and strongly sodic subsoil with higher clay content.

Conclusions

The use of fuzzy k-means and proximal acquired digital data including channels of EM and γ-ray data led to the identification of soil management zones. Using REML analysis and LMM and considering physical (i.e. clay, silt and sand) and chemical (i.e. pH, $EC_{1:5}$, CEC, exch. cations and ESP) properties of the topsoil (0–0.3 m) and subsoil (0.6–0.9 m), the mean squared prediction error (i.e. ⍰^{2}p,C) was minimised when 3 zones were considered for more than half of the soil properties.

Whilst similar zones were generated by clustering percent yield variation over 3 years (i.e. 2014, 2015 and 2016), the ⍰^{2}p,C was larger. The exception was subsoil ESP, which suggests this property has some influence on productivity. Follow up work is required to determine if these rates of application have the desired effect of leading to increased yield. In this regard, the use of strip trials in the zones would be appropriate and at the various prescribed rates to determine if indeed the guidelines are correct.

A full cost-benefit analysis of the results could also be discerned if in subsequent years the yield could be monitored. Monitoring of the soil condition is also imperative, with follow up sampling and analysis required to determine the residual effect of amelioration on improvements in soil condition and quality.

References

Schroeder, B., Panitz, J., Wood, A. & Kealley, M. (2009). Six-Easy-Steps nutrient management completed. Australian Canegrower, 27 July, 10-11.

5.5 Herbert - Improved prediction of soil exchangeable sodium percentage (ESP) using wavelet analysis

(Note: Paper submitted to COMPAG and will be forwarded to SRA on publication)

Introduction

In Australia, soil is considered sodic when the top metre has an exchangeable sodium percentage (ESP) greater than six (> 6 %). Sodicity is a natural feature of Queensland, with approximately 45 % of the state meeting this criterion. While much of the state falls within the category of an arid to semi-arid climate, sodic soil also characterises sub-humid and humid areas owing to soil forming factors that favour accumulation of sodium, including parent material, time and processes of sodium addition from aeolian and cyclical deposition. This is particularly the case in north-east Queensland and along the coastal margin.

Gypsum is the most used ameliorant to reclaim sodic soil, given it provides calcium as a sodium substitute. In sugarcane growing areas of north-east Queensland, the **6ES** ameliorant guidelines (Schroeder et al., 2006) were developed to assist farmers determine suitable rates of gypsum application based on soil ESP.

In the Herbert valley, and as shown in **Table 5.5,** this includes rates of 2 (ESP; 6 – 10 %), 4 (10 – 15 %) and 6 (> 15 %) tonnes per hectare. However, knowledge of spatial variation of ESP cross a field is all but not existent, owing to the high cost and time-consuming nature of sampling and laboratory analysis.

Table 5.5 Gypsum guidelines for sodic soils in Proserpine after Schroeder et al., (2009).

Exchangeable Sodium Percentage (ESP - %)	Sodicity class	Gypsum application (tones/ha)
<6	Non-sodic	0
6 – 10	Sodic	2
10 – 15	Moderately sodic	4
> 15	Strongly sodic	6

At present, conventional soil maps available in many sugarcane areas, like Proserpine, were developed based on soil morphological descriptions that were applied by a soil surveyor to a pre-existing soil classification. Extrapolation using air-photographs, Landsat images or digital elevation models are commonly used to relate the descriptions to the soil forming factors. However, these conventional soil maps seldom provide quantitative soil chemical property (e.g. ESP) information.

Aims: The aims were to compare DSM approaches to predict and manage topsoil (0 – 0.3 m) ESP to see if;

i) Digital data, either alone or in combination can be modelled (LMM) to make a DSM of ESP,
ii) Digital data was decomposed (i.e., D and A) at different scales (i.e. 10, 20, 40 and 80 m) using wavelet analysis, a LMM can predict ESP using D and A components, and
iii) Wavelet components from different digital data to determine which was superior either alone or in combination.

The comparisons between models, calibration sample sizes, digital data were made by using Lin's concordance correlation coefficient (LCCC) and root mean square error (RMSE).

Study area

The study area is located west of Ingham Queensland, Australia and on a Sugar Research Australia farm. Figure 1a shows four fields with a combined area of 7.55 ha; with each field ~130 m in width and in a north-south orientation having combined length of 580 m. Geologically, the area is situated on Quaternary floodplain alluvium (Qha) of clay, silt and sand.

Toobanna is the predominant soil type with the surface a dark loam fine sandy to clay loam. It overlies a conspicuously bleached A2 horizon with a mainly abrupt to clear change to a mottled yellow-brown and brown medium to heavy clay. Sandy D horizons are common. Trebonne is a minor soil type occurring on relict levees of prior and abandoned streams. It is characterized by dark loam fine sand to clay loam fine sand surface and paler A2 overlying a mottled yellow-brown and brown clay loam fine sand.

Results

Figure 5.5a shows DSM generated by LMM using statistically significant raw digital data. While it reflects the predominantly non-sodic (ESP < 6 %) nature of most of the study fields, it does not predict the moderately sodic points in the northern fields nor with any reliability (**Figure 5.5e**).

Figure 5.5b shows DSM of ESP generated using statistically significant D and A components of all three-digital data at 20 m (i.e. Lin's = 0.65). Again, the pattern of non-sodic areas was discerned, with sodic areas identified and represented (i.e. drainage depression) with reduced variance (**Figure 5.5f**).

Figure 5.5c shows ESP generated by using statistically significant D and A components of all three-digital data at 40 m (i.e. Lin's = 0.75). The distribution of non-sodic (< 6 %) areas was small but perhaps problematic given no samples were measured in this range. Nevertheless, the DSM was representative of broad patterns of sodic soil along the drainage depression in the southern fields. It also reflected the two locations of sodic soil in the north. **Figure 5.5g** also shows smaller variance in prediction.

Figure 5.5d shows the DSM of ESP generated using statistically significant D and A components in combination at 80 m (i.e. Lin's = 0.87) of all three-digital data. It was clear that this DSM best reflects the measured ESP. While **Figure 5.5h** shows the smallest variance of all the maps, further work in validation would be required to confirm topsoil ESP was non-sodic and also where it was deemed to be strongly sodic (> 20 %) as these were not measured.

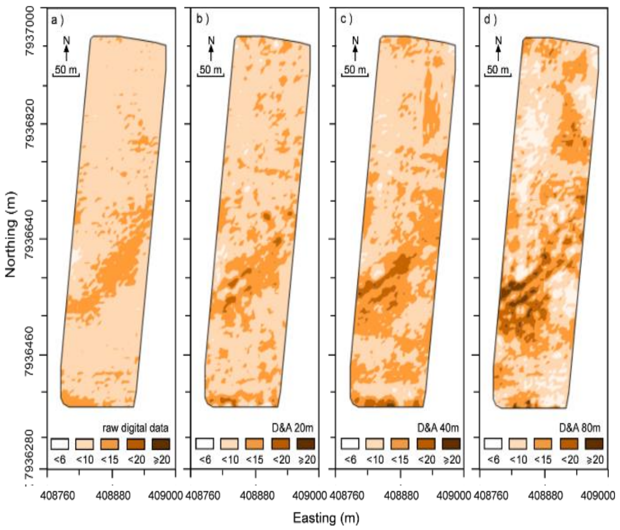


Figure 5.5: DSM topsoil (0 – 0.3 m) ESP (%) using LMM using statistically significant; a) digital data, b) detail (D) components, c) approximate (A) components and d) D and A components in combination.

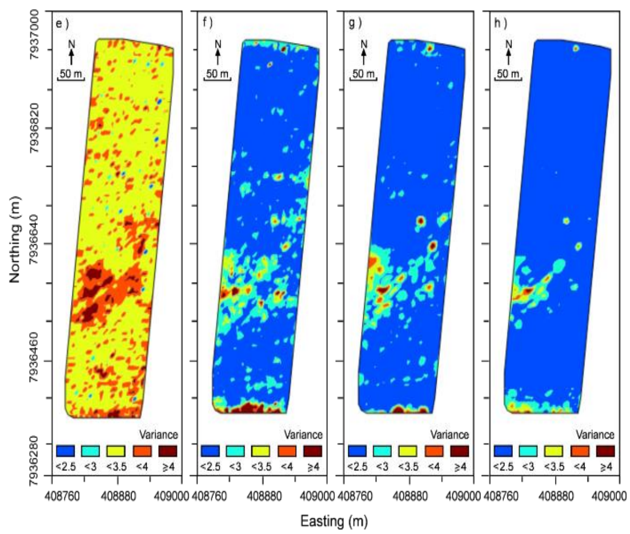


Figure 5.5: DSM topsoil (0 – 0.3 m) ESP (%) using LMM using statistically significant; with prediction variance using e) raw digital data, f) detail components (D), g) approximate components (A) and h) D and A components.

Conclusions

Figure 5.5d offers the prospect of applying the **6ES ameliorant management guidelines** (Schroeder et al., 2009) that were developed to assist sugarcane farmers to determine suitable rates of gypsum application based on topsoil ESP. Given these fields were in the Herbert valley, this DSM indicates areas where the soil was sodic (6 - 10 %), and therefore where a rate of 2 tonnes per hectare of gypsum can be applied to ameliorate this soil condition.

Where the topsoil was moderately sodic (10 – 15 %), a rate of 4 tonnes per hectare gypsum would be recommended. This includes the areas around the two locations in the northern part of the study area. Larger recommendations would be appropriate in the area delineated as strongly sodic (15 – 25 %).

References

Schroeder, B., Panitz, J., Wood, A., Kealley, M., (2009). **Six-easy-steps** nutrient management completed. Australian Canegrower, 10 – 11.

5.6 Herbert - Comparing management zone maps to address infertility and sodicity in sugarcane fields

(See **Appendix 5.6_2019_Arshad_STILL_Zones_CEC-ESP**)

Introduction

In the Herbert Valley, soil texture can influence sugarcane productivity. This is due to the generally coarser textured nature and infertility of the soil given the low cation exchange capacity (CEC – cmol(+)/kg). Because the soil is also characteristically high in exchangeable sodium, another problem is the exchangeable sodium percentage (ESP %), which are at levels considered to be moderately-sodic (i.e. 6-10 %).

To manage these issues, the sugarcane industry developed the **6ES** nutrient and ameliorant guidelines to assist farmers and land managers to determine suitable fertiliser rates (e.g. lime) to add nutrients thereby increasing pH and ameliorants (e.g. gypsum) to mitigate excess sodium (Schroeder et al., 2009). However, these guidelines suggest varying application rates for different levels of CEC and ESP.

In the Herbert valley, and as shown in **Table 5.6** this includes rates of 2 (ESP; 6 – 10 %), 4 (10 – 15 %) and 6 (> 15 %) tonnes per hectare. However, knowledge of spatial variation of ESP cross a field is all but not existent, owing to the high cost and time-consuming nature of sampling and laboratory analysis.

Table 5.6 Lime guidelines for infertile soils in Herbert valley after Schroeder et al., (2009).

Cation Exchange Capacity (cmol(+)/kg)	Lime application (tones/ha)
<3	2.25
3 - 6	4
> 6	5

Conventional soil maps available in many sugarcane areas, like the Herbert, were based on soil morphological descriptions by a soil surveyor to a pre-defined classification. Extrapolation using air-photographs were then used to relate the descriptions to the soil forming factors. However, these conventional soil maps seldom provide quantitative soil chemical property (e.g. ESP) information.

An alternative approach is to use a DSM approach. However, where there is no direct correlation between soil properties (CEC and ESP) and the proximal sensed digital data, an alternative is to try and develop management zones by numerically clustering the digital data.

Aims: The aims of this research was to compare DSM approaches to predict and manage topsoil (0 – 0.3 m) CEC and ESP using management zones (i.e. 2, 3 and 4);

i) Using digital data alone (i.e. elevation, γ-ray & EM) or in combination, using restricted maximum likelihood (REML) analysis and determining the mean square prediction error (MSPE), and
ii) Compare the DSM with a traditional soil texture map (k = 3) and field-based (k = 3) delineations, with results discussed in terms of cost of application of the fertilisers or ameliorants using the DSM of management zones or a one-size fits all approach, which is the current paradigm.

Study area

The study area (18°39’32”S, 146°8’10”E) is located in the Herbert Cane Productivity Services Limited farm, Ingham, Queensland, Australia (Figure 1). We considered three of the fields, delineated by two road-ways (Figure 2a), with the total area covering 7.55 ha with overall dimensions of 580 × 130 m.

Figure 5.6.1a) show these fields are denoted numerically, from north to south as 1, 2 and 3, and covering areas of approximately 3.03, 1.35 and 3.17 ha, respectively. The soil texture has previously been described and mapped across the farm, using a traditional approach (Herbert Cane Productivity Services Ltd.).

Figure 5.6.1b) shows the three different soil textures from a traditional soil map, including; clay in the northern third, silty clay in the northwest corner and centre and terrace silt loam in the south (Wilson & Baker, 1990), covering 2.18, 3.32 and 2.03 ha, respectively.

Results

Figure 5.6.2a) shows the DSM of 2 zones as generated by clustering all the digital data (i.e. elevation, γ-ray and EM), while **Figure 5.6.2b)** shows the DSM of 3 zones.

To predict topsoil CEC, the smallest MSPE (2.20) was calculated using DSM of 2 zones using all digital data **Figure 5.6.2a)**. This was followed by the DSM produced by using only the EM (2.22) and then elevation data (2.29). The CEC DSM as generated by γ-ray data (2.32) was least accurate. The results of the traditional soil texture (3 zones) map was larger (2.37) as was field-based delineation (3 zones) had the largest MSPE (2.41).

To predict ESP, the smallest MSPE (5.60) was using DSM of 3 zones using all data **Figure 5.6.2b)**. Performance of individual data showed EM (6.69) second-best, followed by elevation (6.83) and γ-ray (7.09). The texture map (k = 3) showed the largest MSPE (7.04), while field-based delineations (k = 3) performed well (6.2).

Figure 5.6.3 shows plots of mean and standard error of topsoil (0 – 0.3 m) CEC and ESP, generated by different approaches (i.e. **a)** DSM, **b)** soil texture map and **c)** field-based delineations). For the DSM of CEC, zone 2A (3.0 cmol(+)/kg) and 2B (1.9 cmol(+)/kg) were statistically different. The same was the case for ESP, where zone 3B (11.1 %) was strongly sodic (10 – 15 %), with 3A (8.6 %) and 3C (6.0 %) moderately sodic (6 – 10 %).

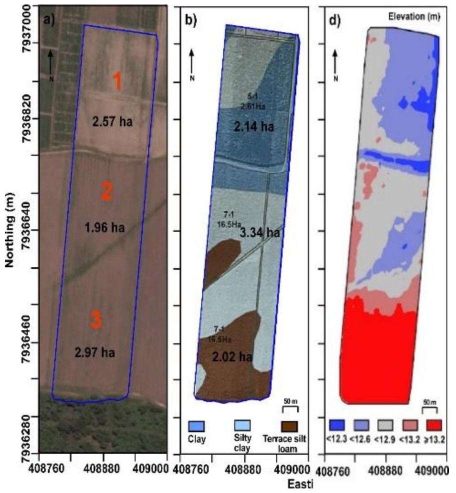


Figure 5.6.1a) Field-based delineations, **b)** soil texture map, and **c)** elevation data (m).

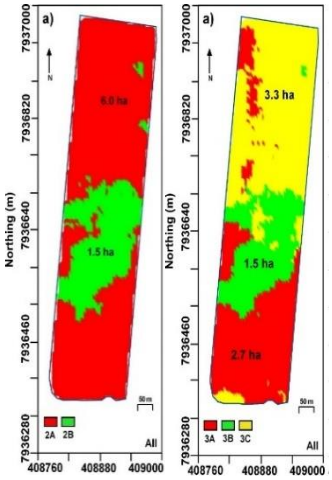


Figure 5.6.2 DSM of **a)** 2, and **b)** 3 zones based on all digital data.

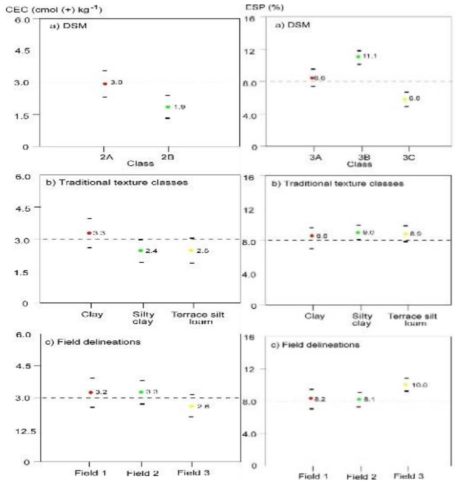


Figure 5.6.3 shows mean and standard error plots of topsoil (0 – 0.3 m) **CEC** and **ESP**.

Considering the results shown in **Figure 5.6.3 (left panel)**, the cost of application of lime to manage CEC showed the DSM approach was most expensive (A$5,670), followed by field-based ($5,040), soil texture map ($4,357) and the standard application rate ($3,937), and based on the 6ES nutrient guidelines (**Table 5.6**).

Considering the results shown in **Figure 5.6.3 (right panel)**, the cost of application of gypsum to ameliorate ESP showed soil texture map (A$3,150) followed by DSM approach of 3 zones (A$3,780) were cheapest, then field-based (A$3,990), and standard application rate (A$3,964) based on **6ES** guidelines (**Table 5.5**).

Conclusions

The issues that remain unresolved were clear and our results point toward future research directions. First, what is cost-benefit of **DSM** approach in terms of improved productivity. Second, how useful were the management guidelines and are they in fact optimal for accounting for the **CEC** and **ESP** in the Herbert valley. In both cases, zones based on DSM approach can be used to test these guidelines and the application rates for lime and gypsum by developing strip trials in each zone, because the zones are uniform.

References

Schroeder, B., Panitz, J., Wood, A., Kealley, M., (2009). **Six-easy-steps** nutrient management completed. Australian Canegrower, 10 – 11.

Wilson, P.R., Baker, D.E. (1990). Soils and agricultural land suitability of the wet tropical west of North Queensland: Ingham area. Land Resource Bulletin-Queensland Dept of Primary Industries (Australia).

5.7 Burdekin - Comparison of digital and conventional soil maps for mapping topsoil exchangeable calcium and magnesium

(See **Appendix 5.7a_2019_Li_Geoderma_Ca-Mg** and **Appendix 5.7b_2019_Li_CATENA_Ca-Mg**)

Introduction

Calcium (Ca) and magnesium (Mg) are important for sugarcane growth and development. The former plays an important role in developing plant roots and leaves. The latter is essential for photosynthesis, given it is the central element of the chlorophyll molecule. In terms of sugarcane production, soil deficient in exchangeable (**exch.**) **Ca** and **exch. Mg** leads to chlorosis, necrosis, curling of plant leaves with ultimate cessation of plant growth.

Given the importance of **Ca** and **Mg**, the **6ES for nutrient management** guidelines in the Burdekin, were developed to ensure the adequate cations. For example, when **exch. Ca** is small (< 0.2 cmol(+)/kg), the lime application rate should be 3 t/ha (**Table 5.7**). Conversely, when **exch. Ca** is large (> 0.8 cmol(+)/kg) the rate of application would be 1 t/ha. Similarly, the guidelines suggest for small (< 0.05 cmol(+)/kg) and large (> 0.2 cmol(+)/kg) **exch. Mg**, rates of application should be 150 and 50 kg/ha, respectively.

Table 5.7 Six-easy-steps nutrient guidelines for sugarcane in the Burdekin district after Schroeder et al. (2009).

Range	**exch. Ca** (cmol(+)/kg)	Lime (tonnes/ha)	**exch. Mg** (cmol(+)/kg)	Magnesium (kg/ha)
Small	<0.2	3	<0.05	150
Intermediate-small	0.2-0.4	2.5	0.05-0.1	125
Intermediate	0.4-0.6	2	0.1-0.15	100
Intermediate-large	0.6-0.8	1.5	0.15-0.2	75
Large	>0.8	1	>0.2	50

Aims: The primary aims of this study was to predict **exch. Ca** and **Mg** using a DSM approach and to determine the best;

i) Mathematical model (i.e. LMM, RK, RF and SVM),
ii) Calibration sample size (n = 10-140),
iii) Set of digital data (i.e. γ-ray and EM) either in combination or alone, and
iv) Transect spacing (i.e. 7.5, 15, 30, 45 and 60 m) for collecting digital data.

The comparisons between models, calibration sample sizes, digital data, and transect spacing were made by using Lin's concordance correlation coefficient (LCCC), root mean square error (RMSE) and mean error (ME).

Study area

The study area was located 24 kilometres to the southwest of Ayr, in Burdekin River Irrigation Area (BRIA), North Queensland. The total study area compromised of ~36 ha with dimensions of 900 × 400 m. The soil at the northern is a relict levee with clay overlaid by sand or loam (Chromosols). The centre of the field is either a yellow-grey duplex soil with sand or loam over sodic clay (Sodosols), interspersed among light to light-medium clay surfaces and self-mulching (Vertosols). The southmost part is a yellow duplex soil with loam over sodic clay (Sodosols) that are alkaline.

Results

To predict either topsoil **exch. Ca** and **Mg** the best model in terms of strongest LCCC and smallest RMSE was LMM, followed by RK, RF and SVM.

A total of 60 calibration samples were enough to develop accurate predictions of topsoil Exch. Ca given all models reached strong LCCC (> 0.8) and RMSE less than half the standard deviation (0.07). A total of 80 calibration samples were also optimal to develop predictions of topsoil **exch. Mg**.

From a farm management perspective, 30 calibration samples with LMM was satisfactory for predict **exch. Ca** (LCCC = 0.83) with 40 (0.84) sufficient for **exch. Mg**.

With respect to the digital data, EM (with LMM and n = 60) was more accurate (RMSE = 0.06), less biased (ME = 0.003) and had stronger LCCC (0.85) compared to making a calibration model with only the γ-ray. However, using both digital data in combination was most accurate (0.05) and had strongest concordance (0.87). Similar findings were observed for **exch. Mg**.

In terms of a suitable transect spacing for collection of digital data to predict topsoil **exch. Ca** or **Mg**, the small transects spacing (i.e. 7.5 m) was recommended, however, the use of 15m and 30m transect spacing also give accurate, unbiased, and precise predictions.

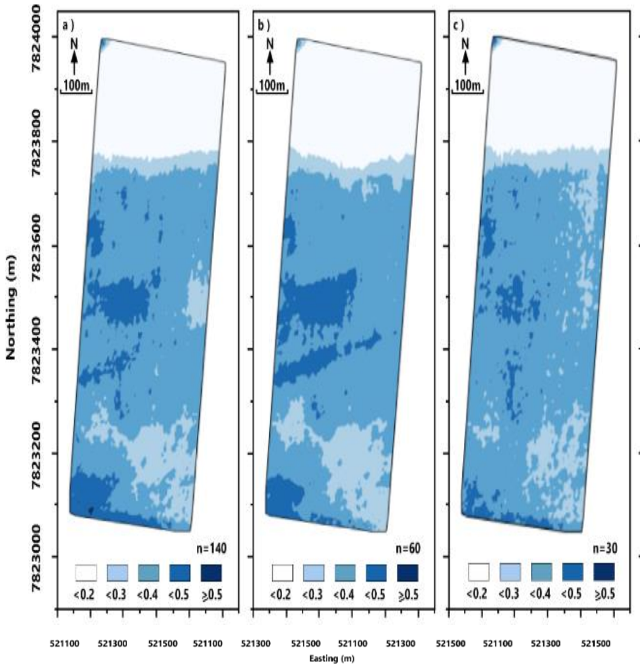


Figure 5.7.1: DSM of **exch. Ca** (cmol(+)/kg) using LMM for calibration sample size **a)** 140, **b)** 60, and **c)** 30.

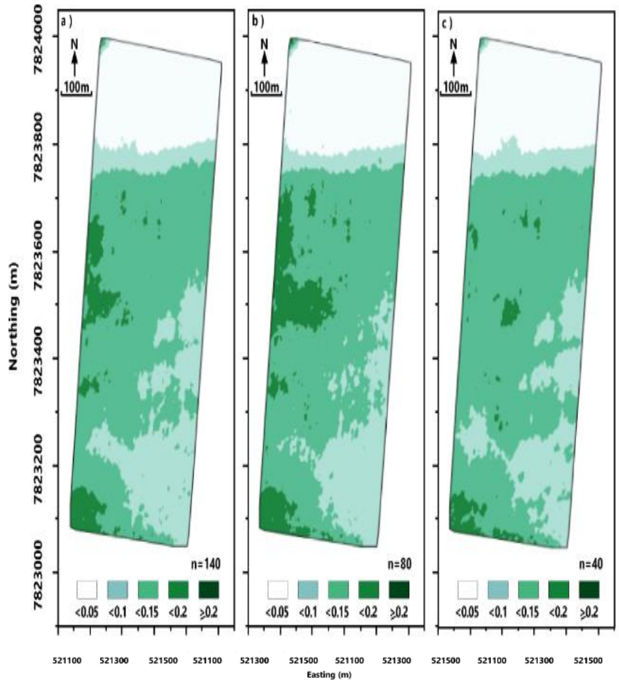


Figure 5.7.2 DSM of **exch. Mg** (cmol(+)/kg) using LMM for calibration sample size **a)** 140, **b)** 80, and **c)** 40.

Conclusions

Figure 5.7.1 shows **DSM**'s of **exch. Ca** The implication for nutrient management for Exch. Ca from these maps was clear. Specifically, and according to the **6ES** (**Table 5.7**), the lime application rate in the northern end of the field should be 3 t/ha given the small **exch. Ca** (< 0.2 cmol(+)/kg). Across the centre and in the south, the lime application rate should be 2.5 t/ha given the **exch. Ca** was mostly intermediate-small (0.2 – 0.4 cmol(+)/kg). However, in several isolated and discrete areas, the application should be 2 t/ha given the **exch. Ca** was intermediate (0.4 – 0.6 cmol(+)/kg).

Figure 5.7.2 shows the DSM of exch. Mg. In terms of nutrient management and application of **6ES** guidelines for Exch. Mg, **Table 5.7** shows the application rate of magnesium in the northern end (<0.05 cmol(+)/kg), and associated with the relict levee, could be 150 kg/ha given the small **exch. Mg**. In the north-east the application rate could be 125 kg/ha where **exch. Mg** was intermediate-small (0.05-0.1 cmol(+)/kg). The magnesium application rate in the various classes identified in the area demarcated in the southern two-thirds should be 125, 100 and 75 kg/ha, depending on intermediate-small, intermediate (0.1-0.15 cmol(+)/kg), or intermediate-large (0.15-0.2 cmol(+)/kg) **exch. Mg**, respectively.

References

Schroeder, B., Panitz, J., Wood, A., Kealley, M., (2009). Six-Easy-Steps nutrient management completed. Australian Canegrower, 10 – 11.

5.8 Proserpine - Comparison of digital and conventional soil maps for mapping topsoil exchangeable sodium percentage

(See **Appendix 5.8_2021_Li_SUM_ESP**)

Introduction

Australian sugarcane is grown in alluvial areas of far north Queensland, where high-rainfall and hot-humid climate produce highly weathered and sodic (exchangeable sodium percentage - ESP > 6 %) soil. The latter is problematic because high ESP increases tendency of soil to disperse after rain. In the topsoil (0 – 0.3 m) this can lead to massive structure, resulting in poor exchange of air, penetration of water and plant roots. Moreover, the soil is susceptible to land degradation via rill and gully erosion.

In the past, soil amelioration consisted of applying uniform rates of gypsum across a field; because it was assumed to be homogeneous. This may lead to under- or over-application. Recently, the **6ES management guidelines** (Schroeder et al., 2009) were developed by the sugarcane industry to assist farmers determine suitable rates for the application of gypsum.

For example, and as shown in **Table 5.8**, when topsoil ESP is non-sodic (i.e., < 6 %) no gypsum need be applied. Conversely, when ESP is strongly (> 15 %) sodic, gypsum application is required to be applied at a prescribed rate of 6 tonnes/ha. Therefore, there is a need for accurate information about the spatial distribution of topsoil ESP to assist amelioration of sodic soil.

Table 5.8 Gypsum guidelines for sodic soils in Proserpine after Schroeder et al., (2009).

Exchangeable Sodium Percentage (ESP - %)	Sodicity class	Gypsum application (tones/ha)
<6	Non-sodic	0
6 – 10	Sodic	2
10 – 15	Moderately sodic	4
> 15	Strongly sodic	6

At present, conventional soil maps available in many sugarcane areas, like Proserpine, were developed based on soil morphological descriptions that were applied by a soil surveyor to a pre-existing soil classification. Extrapolation using air-photographs, Landsat images or digital elevation models are commonly used to relate the descriptions to the soil forming factors. However, these conventional soil maps seldom provide quantitative soil chemical property (e.g. ESP) information.

Aims: The aims were to compare DSM to conventional maps to manage topsoil (0 – 0.3 m) and;

i) Determine minimum number of samples (10, 20, 30,…, 120) to predict topsoil (0 – 0.3 m) ESP using ordinary kriging (OK) of soil samples alone and compare this approach to,
ii) Mathematical models (i.e., LMM, Cubist and Cubist-RK) to relate digital to soil data,
iii) Determine suitable calibration sample size (10, 20, 30,…,120),
iv) Determine suitable set of digital data (i.e. γ-ray and EM) either in combination or alone,
v) Determine suitable transect spacing (7.5, 15, 30, 45 and 60 m) for collecting digital data.

The comparisons between models, calibration sample sizes, digital data were made by using Lin's concordance correlation coefficient (LCCC), root mean square error (RMSE) and mean error (ME).

Study area

The study fields were located 15 km to the northwest of Proserpine, in the Whitsunday Region, Queensland. The study area includes several fields, which are delineated by a road through the centre as well as various drainage channels. A Soil Order map (Hardy, 2003) describes five Soil Orders of the Australian Soil Classification across the area which covers 70 ha with overall dimensions of the study area of 2.8 × 0.25 km,

Figure 5.8.1a) shows that Sodosols characterise the northeast boundary, with Kandosols further to the south. The centre of the study area was characterised by cracking clay Vertosols. South of the road, Kurosols have been mapped and to the south, duplex and less acidic Chromosols can be found. **Figure 5.8.1b)** shows the map of measured topsoil ESP from the 120 calibration soil sample locations.

Results

Prediction of topsoil ESP by OK using only 120 soil samples gave moderate agreement (Lin's = 0.72) with accuracy satisfactory given RMSE (3.69) was less than half standard deviation of measured ESP (½SD = 3.75). Moreover, a minimum number of 100 samples would be required for OK.

However, when digital data was used to value add to soil data in models, the results were equivocal, given Cubist (Lin's = 0.74) and Cubist-RK (0.79) outperformed OK, while LMM (0.65) was inferior. Nevertheless, a smaller sample size of 70 and 60 were required for Cubist and Cubist-RK, respectively to predict topsoil ESP.

In terms of agreement, prediction of topsoil ESP (considering 120 samples) using only γ-ray (Lin's = 0.77) was superior to EM (0.72), however, in combination was best (0.79). The MSPE (n = 120) indicated creating DSM from clustering of digital data was best for 4 zones (see **Figure 5.8.1c**) (MSPE = 27.60), however, Cubist-RK (13.40), Cubist (14.75), OK (15.56) and LMM (15.76) provide better prediction of topsoil ESP.

Nevertheless, all DSM generated smaller MSPE than a conventional Soil Order map (32.33). We recommend using Cubist-RK and both digital data, is the optimal approach to develop a DSM for application of gypsum to implement the **6ES guidelines** for **Proserpine**.

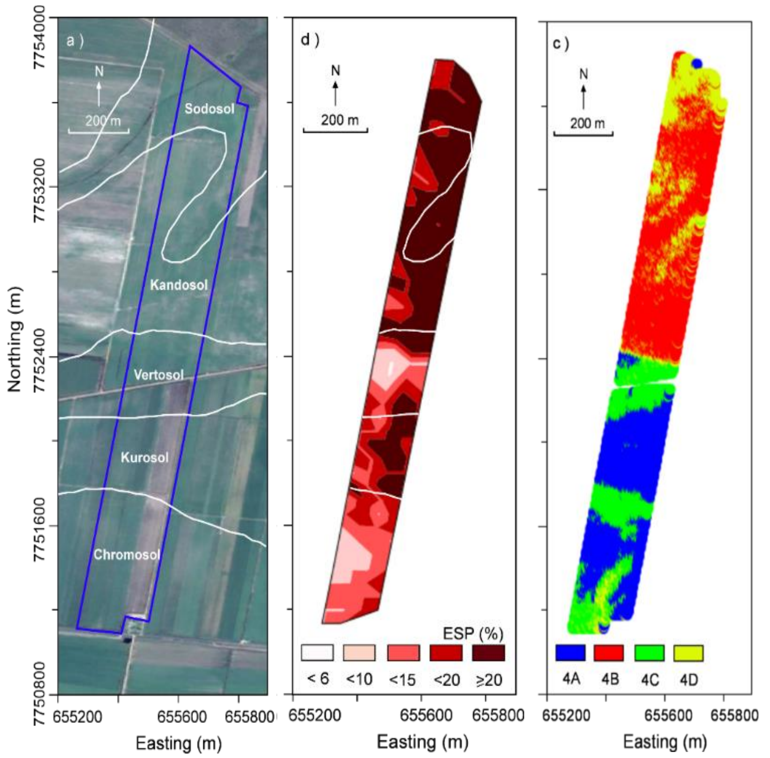


Figure 5.8.1a) Aerial photo of study area with Soil Order, **b)** spatial distribution of measured topsoil (0 – 0.3 m) ESP (%) and **c)** DSM from clustering of digital data for 4 zones.

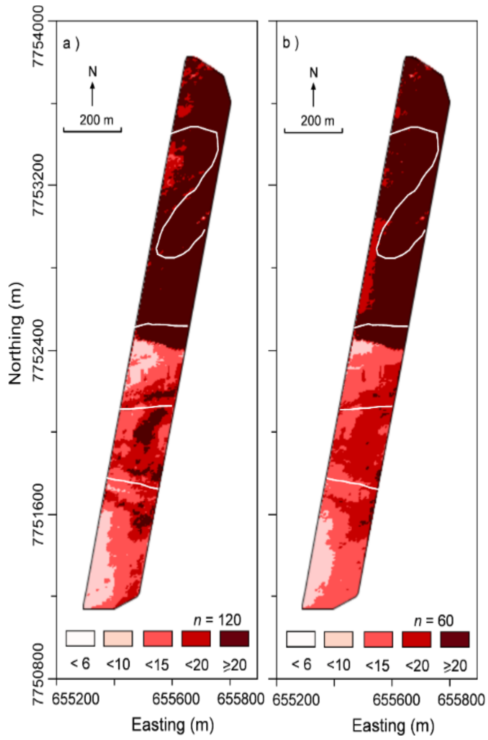


Figure 5.8.2 DSM of topsoil ESP using LMM for calibration sample size **a)** 120, and **b)** 80, calibration soil samples.

Conclusions

Figure 5.82a) and **b)** shows there is not much difference in the DSM developed using either 120 or 80 calibration samples. In terms of applying the **6ES amelioration guideline** for Proserpine district (Schroeder et al., 2009), the strongly sodic (> 15 %) topsoil in the northern half requires 6 t/ha of gypsum to be applied However, small patches of intermediate (10 – 15 %) ESP along the west, only require 4 t/ha. The southern half was characterised by moderately sodic (10 – 15 %) topsoil and a rate of 4 t/ha is recommended.

References

Schroeder, B., Panitz, J., Wood, A., Kealley, M., (2009). Six-easy-steps nutrient management completed. Australian Canegrower, 10 – 11.

5.9 Proserpine - Determination of optimal mathematical model, sample size, digital data and transect spacing to map CEC in a sugarcane field

(See **Appendix 5.9_2021_Li_SUM_ESP**)

Introduction

The cation exchange capacity (CEC) is a measure of how many cations can be retained on soil particle surfaces. It is an important property because it influences soil structural stability, nutrient availability, pH and reaction to fertilisers. To assist farmers balance sugarcane-yield and minimise run-off of fertilisers, the six-easy-steps nutrient management guidelines were developed for the Australian sugarcane growing areas.

In the Proserpine area of Queensland, **Table 5.9** shows that fertiliser rates to negate sandy and low pH soil are recommended and based on the cation exchange capacity CEC (cmol(+)/kg). For example, if CEC is small (< 2 cmol(+)/kg), then 1.25 tonnes/ha of lime would be recommended. Conversely, when CEC is larger (> 8 cmol(+)/kg), 5 tonnes/ha of lime is recommended (after Calcino et al., 2010).

Table 5.9 Lime guidelines for acid soils (when pH $_{water}$ <5.5) after Calcino et al., (2010).

CEC (cmol(+)/kg)	Lime application (tones/ha)
<2.0	1.25
2.0-4.0	2.5
4.0-8.0	4
>8.0	5

Aims: In this research we wanted to test various components of DSM to predict topsoil (0-0.3 m) and subsoil (0.9-1.2 m) and compare;

i) Models (i.e. linear mixed model – LMM, regression kriging – RK, Cubist, random forest – RF, support vector machine - SVM) to relate soil (i.e. CEC) to digital data (i.e. γ-ray and EM),
ii) Digital data used either alone or in combination,
iii) Suitable transect spacing (i.e. 5, 10, 20, 30, 40, 60, 80 m) for digital data, and
iv) Suitable number of samples (i.e. 120, 110,…, 10) for calibration.

These comparisons are assessed using an independent validation (i.e. 40) data set, and evaluated by Lin's concordance correlation coefficient (LCCC) which is a measure of agreement between measured and predicted CEC and accuracy using root mean square error (RMSE). The best DSM of topsoil CEC is used to describe fertiliser application strategy (lime).

Study area

The study area is located approximately 15 km north-west of Proserpine, Queensland, Australia. The study area consists of fields separated by local drainage ways and essentially into a northern and southern half by a roadway. It covers an area of 70 hectares, with dimensions of 2.8 km in the north-south orientation and 0.25 km in the east-west direction.

Results

For topsoil CEC calibration and prediction, the Cubist model with an intermediate number of calibration samples (i.e. 80) using in combination both γ-ray and EM was optimal in terms of agreement (LCCC = 0.79).

For subsoil CEC, a smaller number (i.e. 30) of soil samples for calibration was required to achieve good agreement (LCCC = 0.89). In terms of accuracy, the accuracy (RMSE = 5.42 cmol(+)/kg) of subsoil CEC was satisfactory, as it was less than half standard deviation (SD) (7.55 cmol(+)/kg) of measured subsoil CEC. While not the same for topsoil CEC, the accuracy (RMSE = 1.93 cmol(+)/kg) was not as satisfactory as it was over half measured topsoil CEC SD (1.68 cmol(+)/kg).

The results also showed that while γ-ray alone was superior to EM data for prediction, better results were achieved when both digital data were used in combination.

In terms of a suitable transect spacing for collection of digital data to predict topsoil CEC, the small transects spacing (i.e. 5 m) was recommended. For subsoil prediction, larger transect spacing may still be appropriate (i.e. 5 – 60 m).

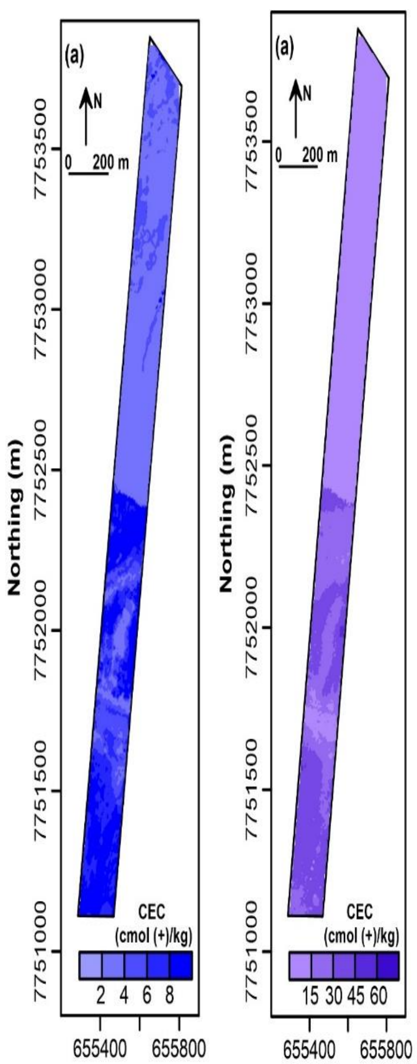


Figure 5.9.1 DSM of **a)** topsoil (0-0.3) and **b)** subsoil (0.6-0.9 m) CEC (cmol(+)/kg) using Cubist and digital data in combination.

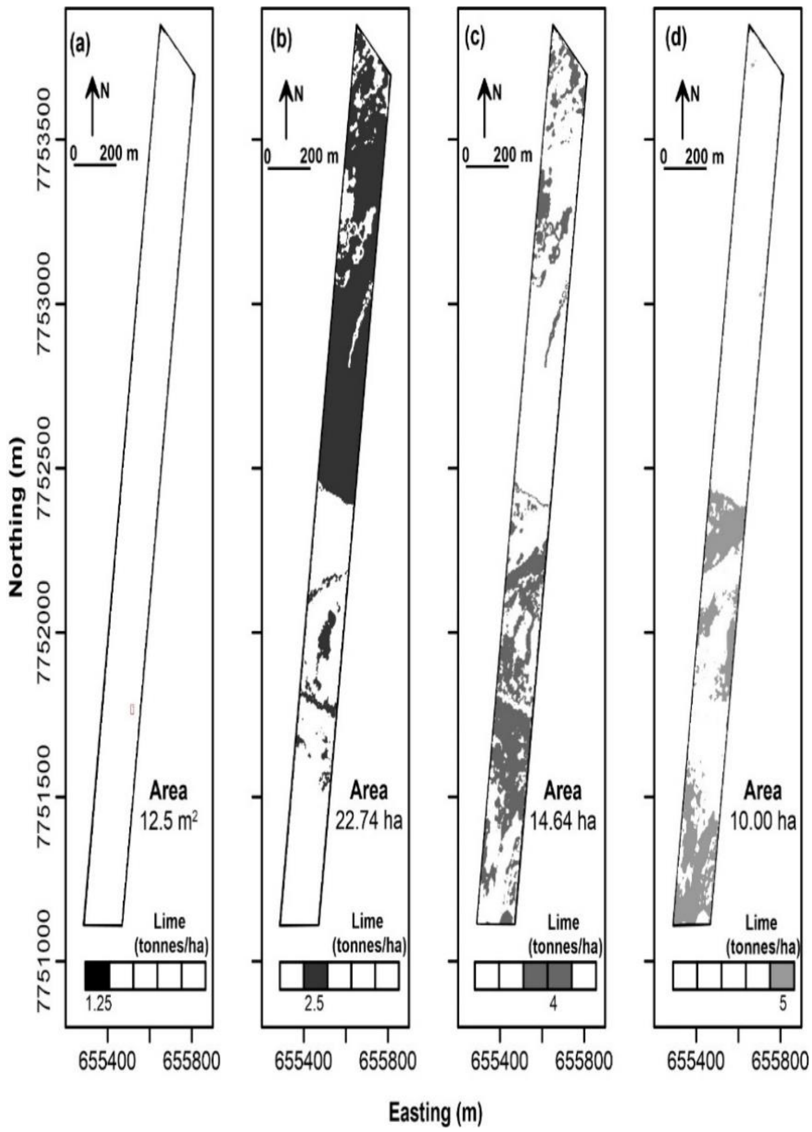


Figure 5.9.2. Spatial distributions of application rate (tonnes /ha) of lime according to the six-easy-steps nutrient management guidelines (Calcino et al., 2010) for topsoil (0 – 0.3 m) CEC predicted using DSM in **Figure 5.9.1a)**.

Conclusions

The DSM approach overall enabled topsoil (**Figure 5.9.1a**) and subsoil (**Figure 5.9.1b**) prediction of CEC with good accuracy and small residuals, particularly at large calibration data sets (i.e. > 80) and a smaller number (i.e. 30) of soil samples, were optimal.

The final DSM of topsoil CEC therefore does allow for the implementation of the **6ES nutrient management guidelines** for lime and as prescribed for Proserpine (Calcino et al., 2010). Specifically **Figure 5.9.2a** shows that the larger northern half (22.74 ha) requires a small (< 2.5 t/ha) application rate with the southern half requiring intermediate (3 – 5 t/ha) to large (5 t/ha) rates of lime.

References

Calcino, D., Schroeder, B., Hurney, A., (2010). Extension and adoption of the six easy steps nutrient management program in sugarcane production in North Queensland, Proc. Int. Soc. Sugar Cane Technol.

6. Key Conclusions (Messages)

Given the results presented in this Final Report and the published research, it can be concluded that the DSM approach can be applied to map various topsoil and subsoil physical (e.g. clay, silt and sand) and chemical (i.e. CEC, Exch. Ca, Exch. Mg and ESP) properties at the field and multi-field scale in different sugarcane growing districts. The final DSM can be used to apply the **6ES nutrient and ameliorant guidelines** in the four sugarcane growing areas investigated and including Mossman, Herbert, Burdekin and Proserpine.

In terms of operational aspects, the following key conclusions can be made;

i) Various soil physical (e.g. clay, silt and sand) and chemical (i.e. CEC, Exch. Ca, Exch. Mg and ESP) properties can be mapped using a DSM approach, but regardless of modelling technique, the number of soil samples required to make a calibration was approximately the same (i.e. 1 sample per hectare) regardless of the soil property (i.e. topsoil Exch. Ca and Mg and ESP) or study area.

ii) Mathematical methods such as LMM are useful when digital data are correlated with soil data, with hybrid methods of machine learning (i.e. Cubist) and regression kriging (Cubist-RK) useful when correlations were statistically significant but not as strong and if residuals were spatially auto-correlated. Alternatively, wavelet analysis can also be useful to predict soil properties (i.e. topsoil ESP) where there was no direct relationship with digital data but a relationship with scale specific variation in digital data (i.e. γ-ray, EM and DEM). Moreover, fuzzy k-means or k-means clustering can be used to make management zones from γ-ray and EM data when the digital data is not directly correlated to the soil data of interest and produce superior predictions than traditional soil texture maps and or using field delineations to predict soil properties.

iii) Digital data of elevation, γ-ray and EM were best used in combination rather than alone, regardless of which modelling technique was considered (e.g. LMM, Cubist-RK and wavelet analysis). In terms of the density of digital data transect spacing, the smaller the spacing the better (i.e. transect every 7.5 m) with a maximum transect spacing of 30 m allowing large areas to be measured in a day (~ 400 ha).

7. Key Outputs

In terms of key outputs, these include;

i) Higher degree training scholarships for 2 PhD (i.e., Nan Li and Maryem Arshad) and 1 Masters of Philosophy (Xueyu Zhao) students, with 4 practicum scholarships (i.e. Xueyu Zhao, Sam Matthews, Jie Wang and Mahboube Mousavifard).

ii) Case studies for development of DSM using soil physical and chemical data and digital data coupled using mathematical models, in four sugarcane growing areas including Mossman, Herbert, Burdekin & Proserpine,

iii) Case study in application of DSM for application of 6ES
   a) nutrient guidelines for N application rate based on SOC (i.e., Mossman),
   b) amelioration guidelines for ESP (i.e., Herbert),
   c) nutrient guidelines for Exch. Ca and Mg and CEC (i.e., Herbert),
   d) nutrient guidelines for Exch. Ca and Mg (i.e., Burdekin),
   e) nutrient guidelines for Exch. Ca and Mg and CEC (i.e., Proserpine),
   f) amelioration guidelines for ESP (i.e., Proserpine),

iv) Legacy soil data including physical (i.e., clay, silt and sand) and chemical (i.e. pH, EC1:5, CEC and exchangeable cations) properties including
   a) Mossman (133 sites at four depths [i.e., 0-0.3, 0.3-0.6, 0.6-0.9, 0.9-1.2 m] in three fields),
   b) Herbert (526 sites at four depths [i.e., 0-0.3, 0.3-0.6, 0.6-0.9, 0.9-1.2 m] in 16 fields),
   c) Burdekin (182 sites at four depths [i.e., 0-0.15, 0.15-0.3, 0.3-0.45, 0.45-0.6 m] in 1 field),
   d) Proserpine (160 sites at four depths [i.e., 0-0.3, 0.3-0.6, 0.6-0.9, 0.9-1.2 m] in 7 fields),

v) Legacy digital data including γ-ray spectrometry (i.e., K, U, Th and TC) and EM (i.e. DUALEM)

8. Future Research (Path to Market)

However, a number of issues need further investigation to improve not only the robustness of the DSM approach but more importantly the use of the DSM for application of nutrient fertilisers and ameliorants according to the **6ES nutrient and ameliorant management guidelines**;

i) With respect to the guidelines, it is necessary to carry out small trials of the application of the guidelines to determine their merit. The DSM developed herein can be used to identify areas of similar topsoil and subsoil properties which have small errors for these strip trial sites to be selected. Owing to the lack of readily available yield monitoring equipment, foliage tests and follow up soil tests, post-application of fertilisers and ameliorants should enable the validation of the DSM and the **6ES nutrient and ameliorant management guidelines**.

ii) It is worth investigating the potential of extrapolation of the models into adjacent areas without collecting extra soil samples. For example, the calibration developed to predict topsoil and subsoil CEC in Helen's Hill (**Section 5.3**) in Ingham should be tested to see if this calibration can be used to predict CEC in adjacent fields. The same applies for the other study areas, given the calibration models in most cases produced a good agreement between measured and predicted soil data.

iii) Moreover, while this project generally investigated implications of DSM approach for topsoil (0 – 0.3 m) properties (e.g. CEC, Exch. Ca, Mg and ESP), the determination of suitable depth for crop growth and identifying subsoil constraints requires an understanding of the amount of nutrients soil can hold and how soil properties vary with depth. Future research should explore the use of making DSM in three-dimensions and using depth functions (i.e. spline, logarithmic and power).

iv) The models used herein could be tested again within a single field, multiple fields or different areas, particularly where there is no strong correlation between the digital and soil data. That is, while strong correlations existed, for example in the Burdekin between digital data and Exch. Ca and Mg, with RK and LMM, machine learning (ML) methods such as SVM can be used to handle the soil and digital data where; the relationships are non-linear, there are outliers, datasets are small and overfitting is problematic.

v) Herein a cLHS approach was used to investigate the use of different calibration samples for DSM modelling. However, other sampling methods are worth investigating and including, but not limited to, spatial coverage sampling, feature space coverage sampling, and simple random sampling (SRS). This is because these sampling methods select sample points with the purpose of evenly spreading locations in geographical space.

vi) The successful implication of wavelet analysis in DSM offers the real prospect of modelling ESP data in an area where the relationships between soil and digital data were weak but where the digital data has subtle scale specific variation. Future research should explore the extrapolation of this approach in adjoining fields and compare other methods for decomposing digital data as used herein and other sources of digital data (i.e. Sentinel 2).

vii) In many case studies, the superiority of different DSM approaches compared to a traditional soil map for predicting soil properties, for example topsoil ESP in 70-ha sugarcane growing area in the Proserpine district, also showed the benefit of such a DSM approach in different fields and for different soil properties such soil physical (e.g. clay and available water capacity) and chemical (e.g. organic carbon and nitrogen) content which have implications in irrigated sugarcane growing areas and for managing and applying nitrogen fertilisers as part of the **6ES nutrient and ameliorant management guidelines**, respectively.

viii) Herein, the use of elevation and proximal sensed γ-ray and EM data were considered for creating DSM of different soil properties or classes. However, it is worth exploring the potential of combining other proximally sensed digital data, such as crop yield, X-ray fluorescent spectroscopy as well as the remote sensed digital data, including Landsat data and Quickbird imagery to assist in the process of DSM. Moreover, different digital data could be compared, either alone or in combination, to determine whether a single source can be used with any accuracy for development of DSM of zones.

ix) While it was shown in separate study areas that an approximate 1 sample per hectare was required to enable the development of a suitable calibration, this is still a large sample size. Research should be conducted in developing cheaper and faster methodologies to enhance or replace conventional soil laboratory measurement. This is because it has been shown that diffuse reflectance spectroscopy (e.g. visible near-infrared, and mid-infrared spectroscopy - visNIR) is rapid, timely, less expensive, non-destructive, straightforward that could be an alternative to conventional soil laboratory measurement. Herein, the number of samples collected in the four different study locations (i.e. Helen's Hill, Burdekin, Proserpine and Ingham) could be used to develop a spectral library and thereby lower costs and time for measuring soil properties, and which could be used to calibrate digital data and predict soil properties and make DSM even more efficient and cheaper. This will particularly be necessary to save on cost of follow-up tests required to monitor soil nutrient and ameliorant levels post-application of the **6ES nutrient and ameliorant management guidelines**.

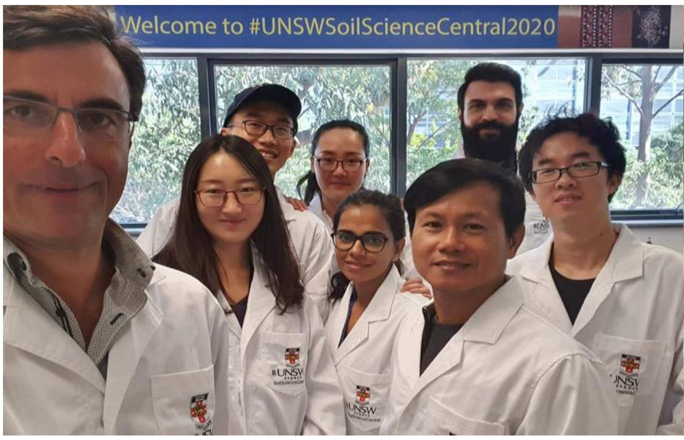
x) The DSM approach has the potential to save costs, however, to date there has been few, if any studies, demonstrating that DSM has not only advantages in agreement and accuracy but in terms of cost-benefit. Specifically, it is worth investigating how the map scale and data collection affect the utility and cost of a DSM and indicates how to decide which particular combination of digital data and map scale will produce the most useful map for a given cost, or will require the minimum cost to achieve a specified precision in DSM.

xi) Soil and digital data sets have been collected in four sugarcane growing areas including **Mossman** (1site covering 3 fields), **Herbert** (5 sites), **Burdekin** (1 site) and **Proserpine** (1 site covering 7 fields). These data will continue to be modelled by three PhD and one MPhil student over the next three years or so. Additional digital data from various airborne (drones) and satellites will be used to compare with and potentially value add to the proximal digital used herein and test their suitability to be used independently to make DSM of the various soil properties studies herein.

xii) Future work will involve the development of short case studies to be published as magazine articles about how a DSM approach can be used in the various sugarcane growing areas to develop information for precision agriculture applications, namely to use of the **6ES nutrient and ameliorant management guidelines**.

9. List of Publications

1. Li, N., Zhao, D., Arshad, M., Sefton, M., Triantafilis, J. (2021). Comparison of a digital soil map and conventional soil map for management of topsoil exchangeable sodium percentage. *Soil Use and Management*, https://doi.org/10.1111/sum.12666
2. Arshad, M., Zhao, D., Zare, E., Sefton, M., & Triantafilis, J. (2021). Proximally sensed digital data library to predict topsoil clay across multiple sugarcane fields of Australia: Applicability of local and universal support vector machine. *Catena 196*, 10.1016/j.catena.2020.104934
3. Zhao, X., Arshad, M., Li, N., Zare, E., & Triantafilis, J. (2020). Determination of the optimal mathematical model, sample size, digital data and transect spacing to map CEC (Cation exchange capacity) in a sugarcane field. *Computers and Electronics in Agriculture*, *173*. doi:10.1016/j.compag.2020.105436
4. Arshad, M., Li, N., Bella, L.D., & Triantafilis, J. (2020). Field-scale digital soil mapping of clay: Combining different proximal sensed data and comparing various statistical models. *Soil Science Society of America Journal*, 84. doi.org/10.1002/saj2.20008
5. Li, N., Arshad, M., Zhao, D., Sefton, M., & Triantafilis, J. (2019). Determining optimal digital soil mapping components for exchangeable calcium and magnesium across a sugarcane field. *Catena*, *181*. doi:10.1016/j.catena.2019.04.034
6. Arshad, M., Li, N., Zhao, D., Sefton, M., & Triantafilis, J. (2019). Comparing management zone maps to address infertility and sodicity in sugarcane fields. *Soil and Tillage Research*, *193*, 122-132. doi:10.1016/j.still.2019.05.023
7. Li, N., Zhao, X., Wang, J., Sefton, M., & Triantafilis, J. (2019). Digital soil mapping based site-specific nutrient management in a sugarcane field in Burdekin. *Geoderma*, *340*, 38-48. doi:10.1016/j.geoderma.2018.12.033
8. Li, N., Zare, E., Huang, J., & Triantafilis, J. (2018). Mapping soil cation-exchange capacity using Bayesian modeling and proximal sensors at the field scale. *Soil Science Society of America Journal*, *82*(5), 1203-1216. doi:10.2136/sssaj2017.10.0356
9. Dennerley, C., Huang, J., Nielson, R., Sefton, M., & Triantafilis, J. (2018). Identifying soil management zones in a sugarcane field using proximal sensed electromagnetic induction and gamma-ray spectrometry data. *Soil Use and Management*, *34*(2), 219-235. doi:10.1111/sum.12410
10. Muzzamal, M., Huang, J., Nielson, R., Sefton, M., & Triantafilis, J. (2018). Mapping soil particle-size fractions using additive log-ratio (ALR) and isometric log-ratio (ILR) transformations and proximally sensed ancillary data. *Clays and Clay Minerals*, *66*(1), 9-27. doi:10.1346/CCMN.2017.064074
11. Wang, J., Zhao, D., Khongnawang, T., Sefton, M., & Triantafilis, J., (2021). Field scale mapping of topsoil organic carbon: In search of optimum digital soil mapping components for nitrogen management across a sandy and infertile sugarcane field in Mossman. *Soil and Tillage Research*, 26102020. Submitted 27 October, 2020.
12. Arshad, M., Zhao, D., Khongnawang, T., & Triantafilis, J. (2021). A systematic evaluation of multisensor data and multivariate prediction methods for digitally mapping exchangeable cations: A case study in Australian sugarcane field. *Geoderma Regional*. Submitted October 5, 2020.



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