HONOURS SCHOLARSHIP REPORT: 2017-18 SEASON

1.	**Project Title**	: Identifying physical and chemical soil constraints in an Australian dryland cotton system.
2.	**Proposed Start Date**	: 01/12/2017
	Proposed Cease Date	: 25/11/2018
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HONOURS SCHOLARSHIP REPORT

1. Executive Summary:

This study examines the effectiveness of publicly-available data to identify farm-scale regions of similarity, and classifies the distribution of physical (available water capacity (AWC)) and chemical (pH and electrical conductivity (EC_e)) soil constraints in a northern NSW dryland cotton system. The incorporated open-source information could identify spatial variability in key soil attributes, though further data accuracy improvements will be increasingly valuable. EC_e (salinity) levels were low, and there was no relationship between AWC and cotton or wheat yield. However, a strongly alkaline pH within a crops capable rooting depth across 70% of the property was identified, with an easily interpretable depth to pH constraint map produced. While depth to pH constraint had a major impact on wheat yield, no impact on cotton yield was observed. Such a discrepancy highlights the importance of analysing multiple years of crop yield monitor data as the most limiting soil constraint may vary based on seasonal conditions. The accurate characterisation of depth to pH constraint across both the property and region will assist in classifying its influence on other crop types and growing seasons in an overall bid to overcome its possible negative implications on productivity and profitability via the adoption of best management practices. Further work will focus on using the developed approach to map the depth to other important soil constraints, such as sodicity.

2. Background:

Spatial and temporal variability in broad-acre cropping environments is a product of soil, climatic and managerial characteristics, plus their interaction. As these elements underpin crop production their characterisation is paramount for the adoption and/or adaptation of best management practices (Whelan *et al.* 2000). In Australian dryland systems available water capacity (AWC) is a primary determinant of crop yield potential. For example, the alluvial plains of northern New South Wales (NSW) are renowned for their suitability for cotton production, largely due to the presence of soil orders with favourable soil moisture retention throughout the profile. Another widespread and well documented factor governing crop yield potential is the presence of soil constraints, with the potential of soil acidity/alkalinity, salinity and sodicity to suppress crop production (Dang *et al.* 2011). With the incorporation of modern digital technologies, the complex nature of broad-acre cropping environments can now be monitored. The wealth of agricultural and environmental data collected directly through on-farm operations and indirectly through governments can assist in identifying and assessing the distribution of physical and chemical soil constraints.

3. Aims and Objectives:

There were 3 aims of this study:

1. Delineate farm-scale regions of similarity using publicly-available data and k-means clustering.
2. Identify farm-scale AWC and chemical soil constraints as they vary laterally across the landscape and vertically within the profile.
3. Conduct a field-scale assessment of the relationship between soil attributes and crop yield.

4. Materials and Methods:

Study site

This study was conducted at '*Llara*' (30°15'18"S, 149°51'39"E), an 1851-ha mixed farming property located near Narrabri, northern NSW. Approximately 1070-ha of the property is designated to broad-acre cropping (dryland), largely due to the presence of fertile Vertosols.

Data sources and k-means clustering

To delineate farm-scale regions of similarity, 20 data layers were sourced and/or calculated from a range of publicly-available government databases. Acquired data layers included digital elevation data from NASA, clay content and gamma radiometrics from Geoscience Australia and NDVI and RED percentile statistics from the USGS Landsat-7 satellite and Google Earth Engine. All data layers were spatially aligned on 5-metre farm-scale standard grid and incorporated in the k-means clustering process. The optimum number of clusters were spatially interpolated on a farm-scale.

Soil sampling, laboratory analysis and clustering statistics

30 soil sampling locations were selected via a stratified random sampling scheme with a clusters spatial extent governing the number of internal sites. All cores were pulled to a depth of 1-metre using a hydraulic drill rig with an attached 50-millimetre tube and subdivided into 5 depth intervals (0-0.1 m, 0.1-0.3 m, 0.3-0.6 m, 0.6-0.8 m and 0.8-1 m). Segregated samples were air dried, ground, measured for the pH and electrical conductivity (EC_e) and scanned by visible and near infrared (VisNIR) using a spectrophotometer with a contact probe attachment. Particle size analysis (hydrometer method) was conducted on the 0-0.1 m, 0.3-0.6 m and 0.8-1 m depth intervals. Existing soil samples from a previous survey were subject to the same methodology. To assess coherency amongst the farm-scale clusters identified, analysis of variance and least significant difference tests were performed separately on sand and clay content, pH and EC_e.

Soil attribute modelling and mapping

A compiled dataset of pH, EC_e, VisNIR spectra and mid-depth variables were incorporated in a Cubist models to predict the sand and clay content of the existing soil samples without textural information. Covariates of digital elevation data, apparent soil electrical conductivity (EC_a) from an EM38 (10-metre), gamma K collected on-farm (10-metre) and NDVI (30-metre) were incorporated in Random Forest models to produce farm-scale maps of sand and clay content, pH and EC_e. Before the modelling process all depth intervals were divided into 1-centimetre depth increments. The hydraulic properties of field capacity (FC) and permanent wilting point (PWP) were calculated using Pedotransfer functions, with the accumulated total of FC-PWP determining an entire profiles AWC. The depth to chemical soil constraint was determined once values surpassed the thresholds of a pH > 9 and an EC_e > 6 dS/m, limiting factors applicable to most broad-acre crops.

Field-scale assessment

A single 183-ha field (Llara 2) was selected, with multi-year crop yield monitor data available (wheat 2016 and cotton 2017/18). The relationship between soil attributes and constraints (if a limiting factor) and crop yield was assessed across these growing seasons via k-means clustering.

5. Results:

Farm-scale regions of similarity and clustering statistics

The methodology identified the optimum number of clusters for this broad-acre cropping environment was 8, with the area accommodated by a single cluster varying from 39-ha to 228-ha. While the amount of significant pairwise differences for each soil attribute was variable the data layers incorporated in the k-means clustering process segregated sand content and EC_e into 5 groups, highlighting variability on a farm-scale. However, the segregation of clay content and pH into 4 and 3 groups respectively suggests a more uniform farm-scale distribution.

Digital soil mapping

In the prediction of sand and clay content the most important covariates were gamma K, NDVI 10th percentile and EC_a. For both Random Forest models the Lin's concordance correlation coefficient (LCCC) was 0.44 and 0.58 respectively, acceptable validation qualities in the realm of digital soil mapping. In the prediction of both pH and EC_e the most important covariate was depth, followed by gamma K for pH and NDVI 10th percentile for EC_e. While the LCCC pH model was favourable at 0.65 the validation quality of 0.29 for the EC_e model was relatively poor.

Farm-scale AWC and chemical soil constraints

The calculation of farm-scale AWC was inevitably influenced by the prediction of sand and clay content, central components of Pedotransfer functions. Structured medium to heavy clay textured soils (Vertosols) have an estimated AWC of 130 mm/m at a full profile. Across 449-ha of this environment the potential AWC was greater than 130 mm/m, though in some localised regions the volume did not exceed 100 mm/m (Fig. 1). The 68-ha of restricted potential AWC coincided with a clay content in excess of 60%, binding water molecules and impeding water accessibility.

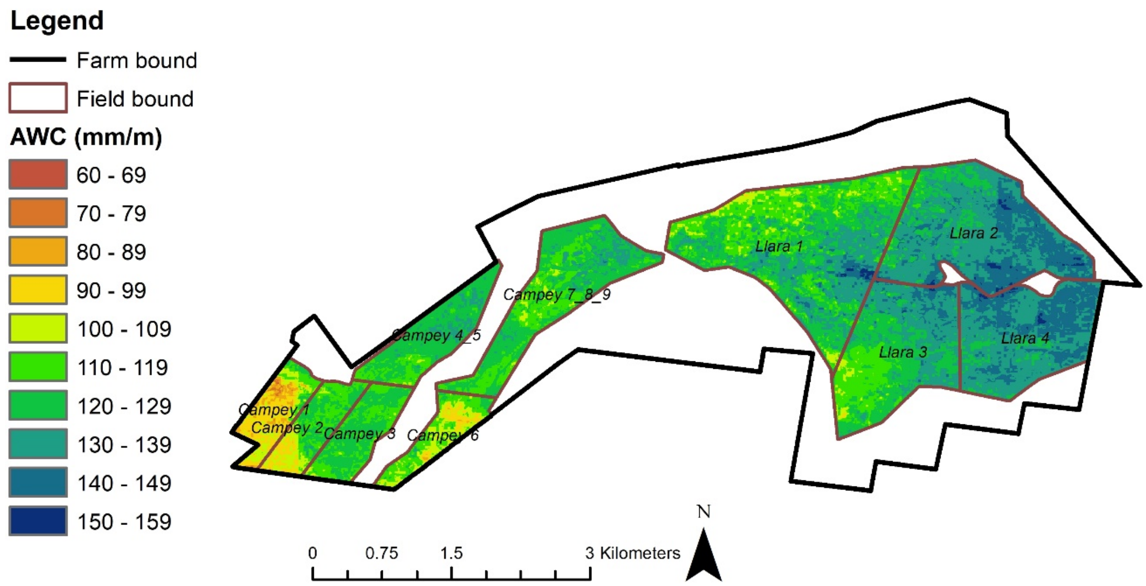

Figure 1 Farm-scale AWC (mm/m) calculated using Pedotransfer functions

744-ha of this environment was constrained as the pH > 9 (strongly alkaline) threshold was surpassed, though where this occurred laterally across the landscape and vertically with the profile varied (Fig. 2). While isolated pockets of the landscape became constrained in the profiles top 20-cms, 610-ha became constrained at a depth of 21-60-cms with a portion of every field influenced. The 326-ha of unconstrained are was generally located across Llara fields 2 and 4. All 1070-ha of this environment was unconstrainted as the EC_e > 6 dS/m threshold was never surpassed.

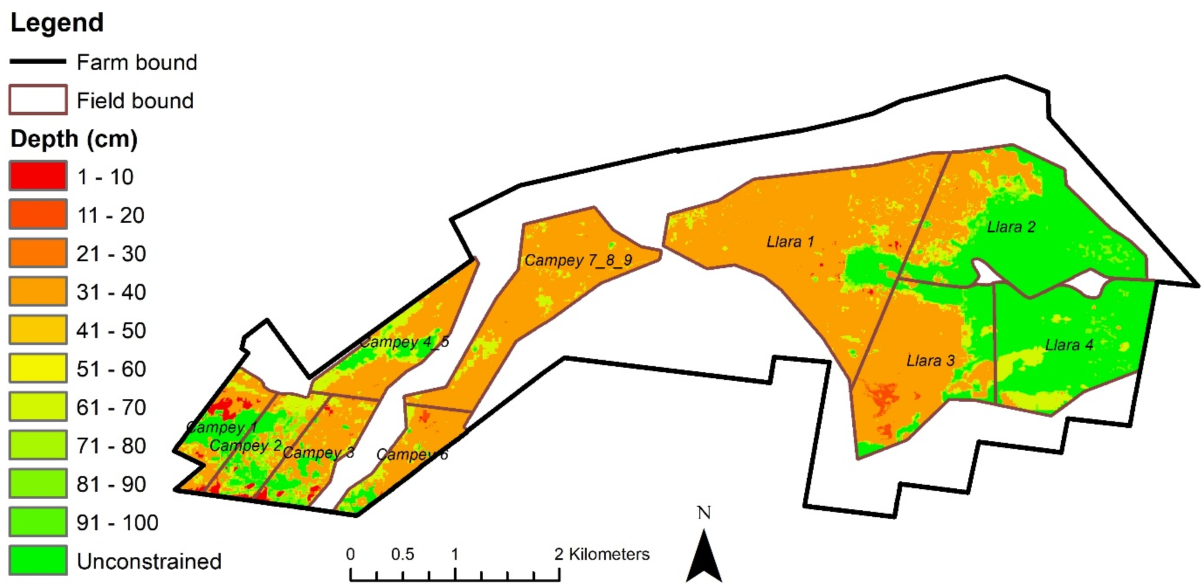

Figure 2 Farm-scale depth to chemical soil constraint (pH > 9)

Field-scale soil-yield relationship

The mean cotton yield of Llara field 2 during the 2017/18 growing season was 3.04 b/ha. A high degree of yield variability exists with no apparent within-field yield trends apart from the north-south orientated contour banks observable in Fig 3. For this field the most appropriate number of clusters for AWC and pH constraint were 3 and 2 respectively. The AWC cluster means (125, 135 and 145 mm/m) displayed in Fig 4 show a moderate degree of spatial structure. The pH constraint clusters (constrained and unconstrained) displayed in Fig 5 show a strong degree of spatial structure with the constrained cluster confined to the north-west region of the field.

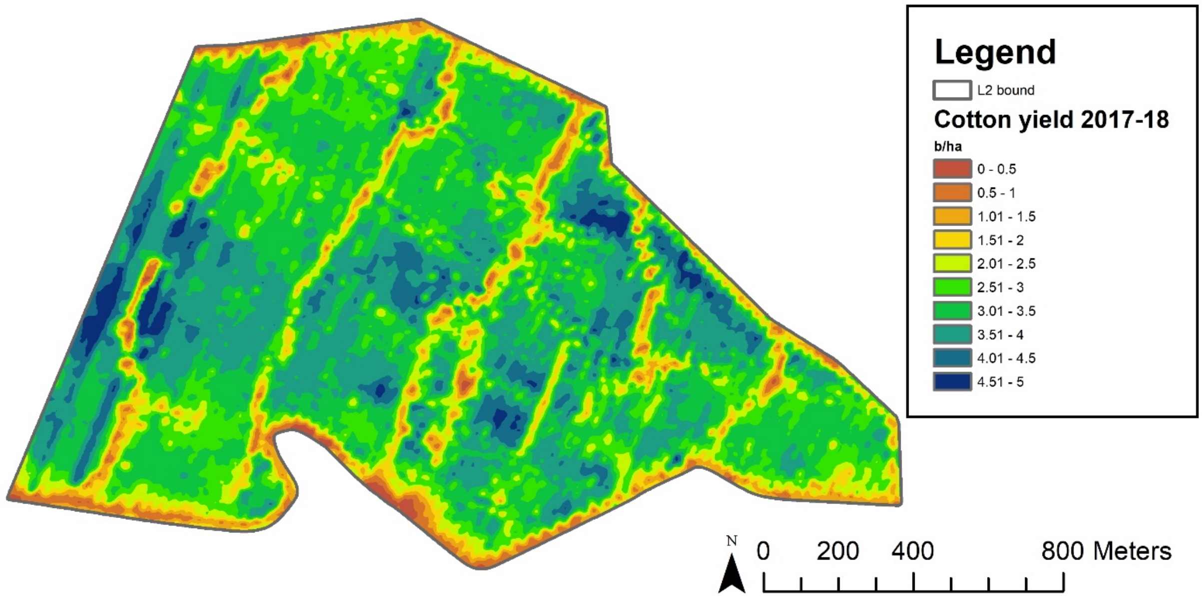

Figure 3 Cotton yield map (b/ha) from the 2017/18 growing season

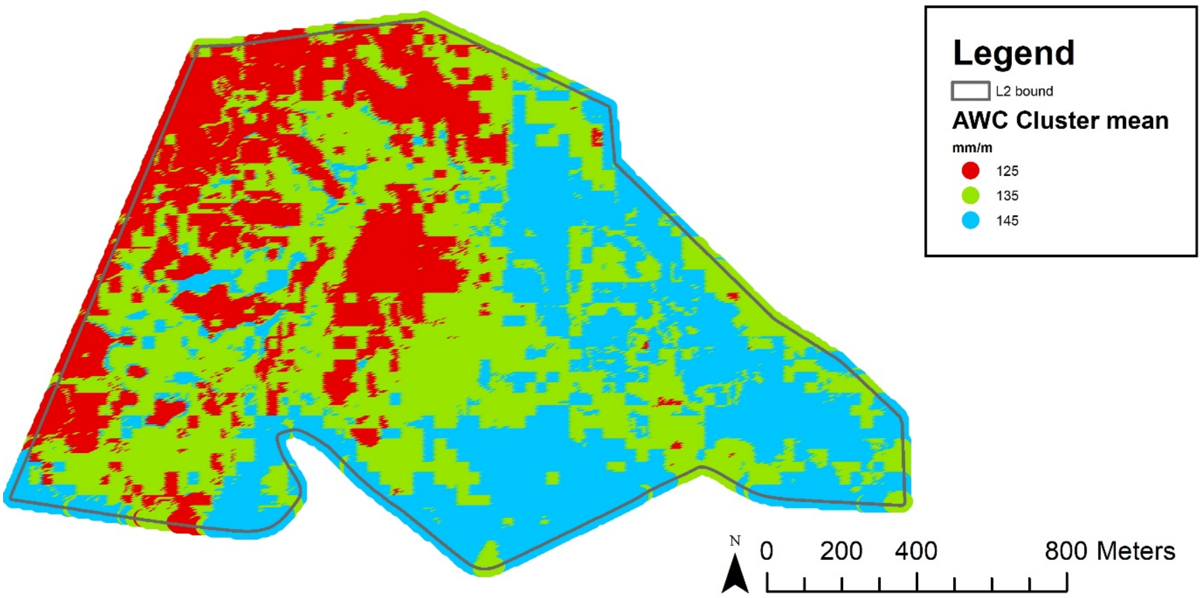

Figure 4 The spatial distribution of 3 clusters derived from AWC data

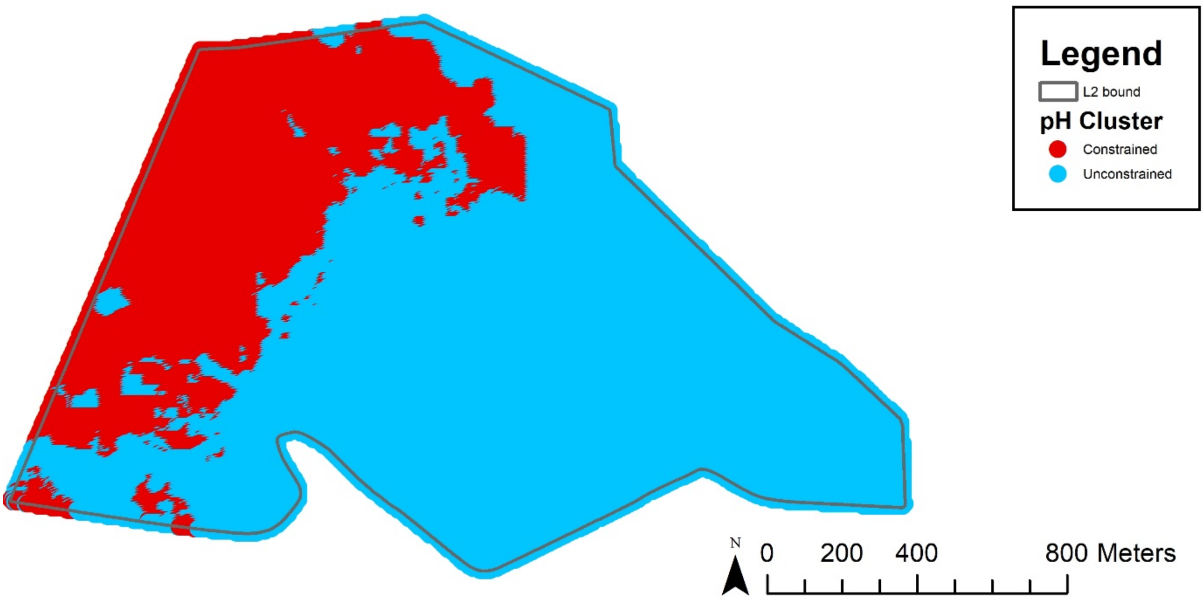

Figure 5 The spatial distribution of 2 clusters derived from a pH > 9

Of the 3 clusters showcasing the relationship between AWC and cotton yield the 125 mm/m clusters yield of 3.18 b/ha was 0.3 b/ha greater than the 145 mm/m clusters. The 135 mm/m clusters yield was 3.02 b/ha. While the pH constrained clusters average yield was 3.15 b/ha the unconstrained clusters yield was 2.96 b/ha. A large distribution in average crop yield was not demonstrated for the relationships between AWC and pH constraint with cotton yield.

However, a secondary assessment between these soil attributes and a 2016 wheat crop returned contrasting results. The 125 mm/m clusters yield was 6.3 t/ha with the 135 mm/m and 145 mm/m clusters yield relatively increasing to 6.59 t/ha and 6.8 t/ha respectively. A large distribution in average crop yield was demonstrated for the pH constraint-wheat yield relationship with the constrained clusters average yield 6.16 t/ha, 0.62 t/ha less than the unconstrained clusters.

6. Discussion and Conclusions:

The incorporation of publicly-available data in the k-means clustering process could effectively distinguish spatial variability in sand content and EC_e in this study. However, similar success may not be demonstrated in other dryland cropping systems as the publicly-available databases utilised often lack reputability. Instead to delineate farm-scale regions of similarity on-farm data should preferentially be selected due to its finer spatial resolution and enhanced accuracy. Quantifying the effectiveness of the methodology via the analysis of a limited number of soil attributes and samples is a major limitation in this study, an issue which should be addressed in the future.

In a dryland production system AWC is a primary determinant of crop yield potential. However, AWC may not correspond with plant available water capacity, a temporally variable soil attribute and commonly the actual determinant of a growing seasons cropping productivity (Hoffmann *et al.* 2017). With reference to this information it would be expected this study's lowest AWC of 125 mm/m would correspond with the lowest cotton yield (2.88 b/ha), however this and other relative results were not apparent. Instead the highest AWC (145 mm/m) coincided with the lowest cotton yield, though there was only a 0.3 b/ha difference in between the 3 AWC clusters. Despite the discrepancy in this study's results the AWC characteristics of Llara field 2 are spatially uniform and highly favourable for crop production compared to other Australian dryland cotton systems.

The influence of soil pH on plant nutrient availability and subsequent cropping productivity has been well documented (Filippi *et al.* 2018). However, in northern NSW dryland cropping systems the identification of other chemical soil constraints has been prioritised as subsoil alkalinity is considered an uncommon issue. In this study the pH constrained clusters average depth was 33 cm, well within the capable rooting depth of both cotton and wheat crops. At a strongly alkaline pH the availability of macronutrients nitrogen and calcium is reduced (Hazelton *et al.* 2007). Coupled with possible aluminium and boron phytotoxicities impairing root growth and development it would be expected a pH > 9 impeding resource accessibility would adversely affect cotton yield (Brautigan *et al.* 2014). Analysis of the pH constraint-yield relationship returned uncharacteristic results as the constrained region coincided with an 0.19 b/ha greater cotton yield.

Fig 3 displays substantial variability in cotton yield with the lack of spatial structure the primary reason why there is no direct correspondence in average crop yield with both the AWC and pH constraint clusters. Overall, this result suggests another or combination of soil attribute/s determined cotton yield during the 2017/18 growing season. Contrastingly, the 2016 wheat crops within-field yield trends were closely associated with the spatial structure of both soil attributes whilst returning characteristic results. A large distribution in average crop yield (0.62 t/ha) with pH constraint clusters suggests this chemical soil constraint primarily governed wheat yield.

To accommodate for within-field spatial variability in soil attributes a management class approach is justifiable for Llara field 2 based on this assessment. However, adopting this best management practice is hazardous given the statistical conflict between crop types and growing seasons. A modern technique to identify temporally stable within-field production regions irrespective of crop type and growing season is remote sensing. Dang *et al*. (2011) successfully inferred the presence of high subsoil chloride concentrations where within-field regions failed to pass an NDVI threshold over consecutive growing seasons. Their methodology is capable of assessing the distribution of chemical soil constraints for all broad-acre cropping fields at Llara.

7. Highlights:

- 20 publicly-available elevation, soil and remotely-sensed data layers incorporated in k-means clustering (unsupervised machine learning) delineated 8 farm-scale regions of similarity.
- Statistical analysis on soil attribute information (collected from 30 soil samples) identified 5 significant pairwise differences in sand content and EC_e amongst the 8 clusters.
- Accurate farm-scale digital soil maps of textural attributes and pH were produced using elevation, on-farm soil and remotely-sensed covariates incorporated in Random Forest models.
- Across 449-ha of the property the potential AWC was greater than 130 mm/m.
- 744-ha of the property was 'constrained' as the pH > 9 (strongly alkaline) threshold was surpassed, influencing plant nutrient availability and possible elemental phytotoxicities.
- Cotton yield from the 2017/18 growing season did not characteristically correspond with AWC and pH constraint clusters due to substantial variability and lack of spatial structure in the yield map, a result suggesting these soil attributes were not primary determinants of cotton yield.
- Remotely-sensed data could possibly identify temporally stable chemical soil constraints.

8. Future Research:

As Llara is a university owned (The University of Sydney) research property, the institution has a continual vested interest in comprehensive on-farm data collection. This study successfully identified physical and chemical soil constraints as they vary laterally across the landscape and vertically within the profile. While assessing the direct relationship between an individual soil attribute and crop yield is necessary, the dynamics of a dryland cropping system are not considered, as there can often be many limiting soil constraints. As no relationship between cotton yield and AWC or pH constraint was observed a combination of soil attributes likely determined crop yield. To explore the effect of multiple proposed soil constraints on crop yield they must be assessed collectively, an objective achievable using AWC and pH constraint data. A strongly alkaline pH may inhibit rooting depth, therefore restricting the volume of soil accessible to the crop which in turn may reduce AWC. By considering the influence of a chemical soil constraint (pH > 9) capping a physical soil constraint (AWC), an 'effective AWC' map can be formulated, which may have a direct relationship with crop yield.

9. Presentations and Public Relations:

The results from this study are being prepared to publish as an article in a peer-reviewed scientific journal. Precision Agriculture, Soil Use and Management, or Agronomy are likely candidates. Parts of this study have been presented at the National Soils Conference in Canberra, November 2018.

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