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# Simulating the effects of saline and sodic subsoils on wheat crops growing on Vertosols

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**Abstract.** Soils with high levels of chloride and/or sodium in their subsurface layers are often referred to as having subsoil constraints (SSCs). There is growing evidence that SSCs affect wheat yields by increasing the lower limit of a crop's available soil water (CLL) and thus reducing the soil's plant-available water capacity (PAWC). This proposal was tested by simulation of 33 farmers' paddocks in south-western Queensland and north-western New South Wales. The simulated results accounted for 79% of observed variation in grain yield, with a root mean squared deviation (RMSD) of 0.50 t/ha. This result was as close as any achieved from sites without SSCs, thus providing strong support for the proposed mechanism that SSCs affect wheat yields by increasing the CLL and thus reducing the soil's PAWC.

In order to reduce the need to measure CLL of every paddock or management zone, two additional approaches to simulating the effects of SSCs were tested. In the first approach the CLL of soils was predicted from the 0.3–0.5 m soil layer, which was taken as the reference CLL of a soil regardless of its level of SSCs, while the CLL values of soil layers below 0.5 m depth were calculated as a function of these soils' 0.3–0.5 m CLL values as well as of soil depth plus one of the SSC indices EC, Cl, ESP, or Na. The best estimates of subsoil CLL values were obtained when the effects of SSCs were described by an ESP-dependent function.

In the second approach, depth-dependent CLL values were also derived from the CLL values of the 0.3–0.5 m soil layer. However, instead of using SSC indices to further modify CLL, the default values of the water-extraction coefficient (kl) of each depth layer were modified as a function of the SSC indices. The strength of this approach was evaluated on the basis of correlation of observed and simulated grain yields. In this approach the best estimates were obtained when the default kl values were multiplied by a Cl-determined function. The kl approach was also evaluated with respect to simulated soil moisture at anthesis and at grain maturity. Results using this approach were highly correlated with soil moisture results obtained from simulations based on the measured CLL values.

This research provides strong evidence that the effects of SSCs on wheat yields are accounted for by the effects of these constraints on wheat CLL values. The study also produced two satisfactory methods for simulating the effects of SSCs on CLL and on grain yield. While Cl and ESP proved to be effective indices of SSCs, EC was not effective due to the confounding effect of the presence of gypsum in some of these soils. This study provides the tools necessary for investigating the effects of SSCs on wheat crop yields and natural resource management (NRM) issues such as runoff, recharge, and nutrient loss through simulation studies. It also facilitates investigation of suggested agronomic adaptations to SSCs.

**Additional keywords:** subsoil constraints, simulation, crop lower limit, salinity, sodicity, chloride.

## Introduction

Crops growing on Vertosols (Isbell 1996) in Australia's northern grains zone are constrained by several subsoil factors. These factors, collectively referred to as subsoil constraints (SSCs), include high salt concentrations in the soil solution, increased osmotic potential of the soil water, toxic concentrations of chloride (Cl), high sodicity and an associated deterioration of soil physical properties and, to a lesser extent, acidic subsoils

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containing toxic levels of aluminium (Dang *et al*. 2006*a*). Currently there does not appear to be an economically viable soil amelioration option, and genetic solutions through breeding of tolerance to these SSCs seem a long way off. This leaves farmers with the option of learning to live with this problem by developing adaptive management solutions. If the effects of SSCs can be realistically modelled then simulation may provide a promising approach for scientists to develop a more quantitative understanding of the effects of these SSCs and to experiment with management options. For example, Hochman *et al*. (2004) proposed that the net effect of SSCs on wheat (*Triticum aestivum* L.) can be accounted for by consideration of their effect on CLL (soil moisture profile determined when a wheat crop can extract no more moisture from that soil) and thus on the PAWC of a soil (the maximum amount of stored moisture that is available for growing a wheat crop). This proposition enabled them to use the Agricultural Production Systems Simulator (APSIM; Keating *et al*. 2003) to predict both crop production and natural resource management (NRM) effects of various levels of SSCs over a range of locations.

An emerging consensus from work with soils in southern Australia is that the effect of the variable combinations of subsoil constraints in those soils was to reduce plant-available water by increasing the lower limit of cereal crops' available soil water (Hochman *et al*. 2002; Sadras *et al*. 2003; Nuttall *et al*. 2005; Rodriguez *et al*. 2006). This observation is the working hypothesis for this paper. However, the chemical constraints that characterise northern soils (Dang *et al*. 2006b) were found to have significantly different levels and combinations of subsoil constraints when compared with those described in the southern studies. For example, in the current study, the mean value of EC at 0.7–0.9 m depth was 1.6 dS/m, which exceeds the maximum value of 1.31 dS/m in Sadras *et al*. (2003). By contrast, the highest boron concentration in our dataset was only 6 mg/kg compared with 29 mg/kg in Sadras *et al*. (2003). These differences suggest the need for the working hypothesis to be tested on soils in the northern grain zone.

The first objective of this research was to test, for soils in the northern grain zone, the hypothesis that the net effect of SSCs on wheat crops can be accounted for by consideration of their effect on CLL and thus the PAWC of a soil. The corollary of this hypothesis is that if CLL of a soil with SSCs is measured, then simulation (using measured CLL) of a wheat crop grown on it would require no further adjustment for the fact that the crop was subject to SSCs. This hypothesis may therefore be tested by measuring and simulating wheat grain yields at a large number of sites with measured CLL values. A reasonable test of the hypothesis would be a comparison of the correlation of simulated and observed yields at these sites against the benchmark correlation that was obtained with the Queensland dataset that was used in the development of the APSIM wheat crop module, i.e. RMSD = 0.74 t/ha with $R^2 = 0.8$ (Wang *et al*. 2003).

Determining CLL (Dalgliesh and Foale 1998) is a slow and labour-intensive process. Consequently, the number of soils that can be measured is likely to remain limited. A more cost-effective means of accounting for similar soils with varying levels of subsoil constraints must be developed if we are to have a capacity to simulate options for management of paddocks (or management zones for Precision Agriculture) in accordance with their levels of subsoil constraints. Currently, APSIM does not have a specific capability for simulating the effects of salinity and sodicity on crop growth. Two relatively simple options for adding such a capability are investigated in this paper. In the first approach the CLL of soils was predicted: CLL of the 0.30–0.5 m soil layer was taken as the reference CLL of a soil regardless of its level of SSCs, while the CLL of soil layers below 0.5 m depth was assumed to be a function of the 0.3–0.5 m CLL as well as of soil depth and of one of the SSC indices EC, Cl, ESP, or Na. In the second approach, a depth-dependent CLL was also derived from the CLL of the 0.3–0.5 m soil layer. However, instead of using SSC indices to further modify CLL, the default value of the water-extraction coefficient (kl) of each depth layer was modified as a function of SSC indices. Kl is a combined soil (k, representing diffusivity) and crop (l, representing root length density) function that defines the potential water-extraction rate from a soil layer (Meinke *et al*. 1993; Robertson *et al*. 1993*a*, 1993*b*).

## Methods

### *Field experiments*

Thirty-three paddocks with grey, brown, and red cracking clays (Vertosols; Isbell 1996) were selected for this study. They included 6 sites in southern Queensland and 13 sites in northern New South Wales in 2003, plus 14 sites in southern Qld in 2004. All the Qld sites were sown with wheat cv. Baxter, wheat varieties sown at the NSW sites included H45, Wollaroi, Yallaroi, Babbler, Hybrid Meteor, Strzelecki, and Sunbrook. All sowing, harvesting, and crop management operations were carried out using the co-operating farmers' equipment, and planting rates and other management practices followed the accepted district practice. All crops were well managed, with no significant weeds, pests, diseases, or nutrient deficiencies experienced. A more detailed description of field experimental protocols is provided in Dang *et al*. (2006*b*).

All sites were sampled to determine their PAWC characteristics using the methods of Dalgliesh and Foale (1998). Briefly, the drained upper limit (DUL) was determined by wetting up an area of soil until it reached saturation, allowing time for drainage, and then sampling for soil water content in 7 depth intervals (0–0.1, 0.1–0.3, 0.3–0.5, 0.5–0.7, 0.7–0.9, 0.9–1.1, and 1.1–1.3 m). For determining CLL, a rain-exclusion tent for each crop at each site was erected over a portion (3 by 3 m area) of the vigorously growing crop, at the time of anthesis, and was left in place until the crop reached maturity. Soil water content was measured at the time of installation of the rain-exclusion tent and at crop maturity, to determine water-extraction patterns and CLL. PAWC was obtained as the difference between DUL and CLL.

In April–May, soil samples were taken using a 50-mm-diameter tube and a hydraulic sampling rig. Seven depths were examined in the segments: 0–0.1, 01–0.3, 0.3–0.5, 0.5–0.7, 0.7–0.9, 0.9–1.1, 1.1–1.3, and 1.3–1.5 m or to maximum depth of root penetration. Each soil segment was separately dried at 40°C in a forced-draught oven and ground to <2 mm. Soil pH, EC, Cl, and $NO_3$-N were determined in a 1 : 5 soil : water suspension (Rayment and Higginson 1992). Exchangeable cations ($K^+$, $Na^+$, $Mg^{2+}$, and $Ca^{2+}$) were determined by method 15C1 (Rayment and Higginson 1992). The extracts were analysed for exchangeable cations on an inductively coupled plasma-optical emission spectrometer. Exchangeable sodium percentage (ESP) was calculated as the ratio of exchangeable Na to the cation exchange capacity. Soil organic carbon was determined (for use in simulation) by the method of Walkley and Black (1934) and multiplied by a factor of 1.3 to allow for incomplete recovery of carbon by this method.

### *Modelling experiments*

#### *Experiment 1*

This experiment was a test of the hypothesis that the net effect of SSCs on wheat crops can be accounted for by consideration of their effect on CLL and thus the PAWC of a soil. The corollary to this hypothesis is that if CLL of a soil with SSCs is measured, then simulation of a wheat crop grown on it would require no further adjustment for the fact that the crop was subject to SSCs. To test this corollary the APSIM model (Version 5.0), configured with the modules Wheat, SOILN2, SOILWAT2, and RESIDUE2, was used to simulate wheat yield in response to the environmental and management factors at the 33 field sites.

Meteorological data were collected from the nearest meteorological station, using the Silo Patch Point Dataset (Jeffrey *et al.* 2001) to obtain daily records of maximum and minimum temperatures, solar radiation, and vapour pressure. Rainfall data were obtained from on-farm records. Input data for simulation included: cultivar, date of sowing, seedling density, dates and rates of nitrogen fertiliser, initial soil moisture and soil nitrate levels for each layer, and the date of measurement of these values. Measured CLL values were used for all layers below 0.3 m depth. Because of the difficulty in differentiating experimentally between soil evaporation and moisture extracted by crop transpiration in the top 0.3 m, and since most Vertosols have no obvious differences in their morphology in the top 0.5 m, the CLL of the layer between 0 and 0.3 m depth was assumed to be equal in value to the 0.3–0.5 m layer. A standard parameterisation of the model was applied to all unmeasured parameters at all sites and the yield results of the APSIM simulations were tested against observed plot yields. For a full specification of the settings applied to APSIM, see Accessory Publication.

#### *Experiment 2*

This experiment was designed to develop a method for estimating CLL of soils with SSCs in order to simulate the effects of SSCs on wheat crops without measuring the CLLs of every paddock or management zone. The simulations in this experiment differed from Expt 1 in the following two respects.

(1) Measured CLL values were assumed to be unavailable and were replaced by 'reference CLL values'. Reference CLL values are notionally CLL values of a soil that is similar to the measured soil in every respect except that it does not have the SSCs that restrict the CLL of the measured soil. The reference CLL values for each of the 33 soils were derived by leaving unchanged the CLL values of soil layers in the 0–0.5 m range on the assumption that they were relatively free of SSCs, while CLL of soils deeper than 0.5 m depth were estimated as a function of the CLL of the 0.3–0.5 m soil layer and modified as a function of soil depth, based on the established pattern of increasing CLL values with increasing soil depth, which is characteristic of Vertosols (Hochman *et al.* 2001).

(2) The reference CLL values were multiplied by alternative SSC factors. Each SSC factor was optimised separately as a function of each of the SSC indices (EC, Cl, exchangeable Na, and ESP). The estimated CLL values of each alternative SSC indicator were then compared with the measured CLL values for all soil depths below 0.5 m. Exponential functions that minimise the RMDS between measured and predicted CLL were chosen after solutions based on linear functions were rejected on the basis that linear functions were optimised on cut-off values (the concentrations of SSC indices at which CLL = DUL) that were too low when compared with measured data.

#### *Experiment 3*

This experiment was designed to develop a kl-based approach to simulating the effect of SSCs on wheat crops without measuring CLL for every paddock or management zone. As in Expt 2 the measured CLL values were assumed to be unavailable and were replaced by 'reference CLL values'. Reference CLL values for each of the 33 soils were derived by leaving unchanged the CLL values of soil layers in the 0–0.5 m range, while CLL values of soils deeper than 0.5 m depth were estimated as a function of the CLL of the 0.3–0.5 m soil layer and modified as a function of soil depth. In contrast to Expt 2, the CLL values were not further modified as a function of SSC indices. Instead the standard soil depth-dependent kl values were modified by a SSC stress factor. The SSC stress factor was alternatively optimised for each of the following SSC indices: EC, Cl, exchangeable Na, and ESP. Each stress factor was an exponential function of the SSC index that minimised the RMSD between measured and predicted grain yield. The simulated grain yield results obtained by using each optimised index were then compared with the observed grain yields at the 33 field sites. To investigate whether the kl approach results in water uptake patterns that are similar to those observed with the measured CLL approach, the simulated soil moisture values that were obtained from Expt 1 both at anthesis and at harvest were subsequently compared with the values obtained in Expt 3.

### *Statistical comparison of observed and predicted data*

No single statistic gives an adequate overall measure of the goodness-of-fit between observed and simulated values. We chose to present the coefficient of determination ($R^2$) as a measure of the association between observed and predicted values and the root mean squared deviation (RMSD) as an indicator of deviations from the expected 1 : 1 line. All optimisations in this study (Expts 2 and 3) were carried out iteratively with the aid of simple visualisation tools developed in Microsoft Excel® to facilitate rapid viewing (visual assessment of the function as well as observed and predicted data and objective measures of $R^2$ and RMSD values) of effects of parameter changes on goodness-of-fit of observed and simulated results.

## Results and discussion

### *Soil analysis*

The selected sites varied in the extent and type of SSCs present. This is illustrated by the means, medians, standard deviations, and ranges of values measured for pH, EC, Cl, and ESP at 0.7–0.9 m depth (Table 1). Of the 33 soils, 15 soils had EC $>0.9$ dS/m; 13 soils had Cl $>600$ mg/kg. Four of the 33 soils did not have Na or exchangeable cation measurements. Of the remaining 29 soils with measured Na and ESP values, 27 soils had exchangeable Na values $>5.0$ $cmol_c$/kg, and 26 soils had ESP values $>15\%$. Six soils had all 4 parameters over these threshold values and only 4 soils were below all these threshold values. Only one soil with $pH < 5.5$ was above all the other threshold values. Soil pH was therefore excluded from further consideration in this study. The pronounced difference between mean and median EC values is indicative of a skewed distribution of soils with respect to EC values. This is due to the presence of several soils with very high EC values associated with the presence of gypsum.

The correlation coefficients for the various chemical indicators of subsoil constraints EC, Cl, ESP, Na, and soil depth are summarised in Table 2. The high correlation coefficient value for Na and ESP is consistent with the observations of Irvine and Reid (2001) and was not surprising since Na is a component of ESP. The low correlation coefficients between EC and Cl and EC and ESP are consistent with the confounding effect of the presence of gypsum in some of these soils. The covariance between Cl, Na, and ESP must be considered when attempting to determine the separate influence of any of these chemical parameters on observed SSCs. Similarly, the known effects of soil depth on CLL (and kl value) of Vertosols are difficult to separate from the effect of chemical constraints on CLL.

### *Experiment 1: Measured CLL as index of SSC*

The range of observed grain yields harvested at these sites was 0.97–5.70 t/ha. Figure 1 shows the performance of the APSIM model when measured PAWC data are used and no specific parameter is employed to account for SSCs. The model accounted for 82% of the observed variability in grain yield with a RMSD of 0.50 t/ha. All attempts to improve the model's performance by using functions based on Cl, EC, or ESP to restrict root development (via the root expansion factor) did not improve on these simulation results.

Given that the performance of APSIM in simulating grain yields for the 33 subsoil constrained sites in this study was at least as good as that reported by Wang *et al*. (2003) for Queensland soils without SSCs, we continue to hold the view that SSCs affect wheat crops primarily by increasing their CLL and thus reducing the PAWC. Confirmation of this hypothesis supports the use of simulation as a tool for exploring the implications of SSC (expressed as reduced PAWC) on production and NRM issues such as those explored by Sadras *et al*. (2003), Hochman *et al*. (2004), Farquharson *et al*. (2006) and Rodriguez *et al*. (2006). This result leaves unresolved the question of predicting the effect of measured SSC indices, such as EC, Cl, and ESP on CLL with sufficient accuracy to adequately predict their effects on yield and soil water dynamics. Experiments 2 and 3 explore this issue.

### *Experiment 2: Replacing measured CLL with depth limited CLL and direct modification of CLL by SSC indicators*

#### *(a) Determining depth limited CLL*

The depth modified CLL function was determined through the following steps.

(1) $LL_i$ is the CLL of the 0.3–0.5 m layer for each soil. This is the soil's reference CLL value.
(2) CLL was assumed to be equal to DUL at Dmax.
(3) For layers between 0.5 m and 1.5 m depth, $CLL_d$ was calculated as:

$$CLL_d = CLL_{0.3-0.5} + f_d \quad (1)$$

where $f_d$ is the depth factor calculated as:

$$f_d = (DUL - LL_i) * (1.0 - [D_{par}e^{(Dmax-d)/(1.5-0.4)}]) \quad (2)$$

where d is depth (m) of the middle of the soil layer, and $D_{par}$ is the depth parameter that determines the curvature of the line describing the increase in CLL as a function of depth.

The optimal parameter value (the value that minimises the RMSD of observed CLL values) determined for Dmax was 1.3 m and $D_{par}$ was optimised at 0.355.

Figure 2*a* shows a comparison of measured CLL values with the calculated $CLL_d$ values as determined above, with no specific parameter used to account for SSCs. This model accounted for 67% of the observed variability in CLL with a RMSD of 0.038. This result is consistent with the fact that depth is a significant predictor of CLL in chemically unconstrained soils and with the positive correlation of chemical constraints and soil depth shown in Table 2. The challenge is to separate these 2 factors and thus improve the prediction of CLL as a function of depth and of SSCs. Iterative optimisation of the depth function in conjunction

**Table 1. A comparison of mean, median, standard deviation, and range of subsoil constraint indicators measured at the 0.1–0.3 m and at 0.7–0.9 m depth layers of 33 soils**

Values in bold are in excess of threshold values (mean, median, and maximum values only)

| | Mean | | Median | | s.d. | | Minimum | | Maximum | |
|---|---|---|---|---|---|---|---|---|---|---|
| Depth (m) | 0.1–0.3 | 0.7–0.9 | 0.1–0.3 | 0.7–0.9 | 0.1–0.3 | 0.7–0.9 | 0.1–0.3 | 0.7–0.9 | 0.1–0.3 | 0.7–0.9 |
| EC (dS/m) | 0.33 | **1.6** | 0.22 | **0.81** | 0.48 | 1.6 | 0.07 | 0.19 | **2.88** | **5.8** |
| Cl (mg/kg) | 69 | 566 | 40 | 496 | 88 | 492 | 1 | 1 | 358 | **1985** |
| Na ($cmol_c$/kg) | 2.58 | **6.63** | 2.46 | **6.10** | 1.26 | 3.38 | 0.01 | 0.18 | **5.99** | **21.0** |
| ESP (%) | 8.3 | **22.0** | 8.4 | **22.7** | 4.3 | 9.6 | 0.1 | 0.38 | **17.2** | **48.8** |
| pH | 8.38 | 7.79 | 8.48 | 7.90 | 0.58 | 1.14 | 7.04 | **4.76** | 9.2 | 9.50 |

**Table 2. Correlation matrix for soil chemical properties and soil depth observed in 33 soils**

| | EC | Cl | ESP | Na |
|---|---|---|---|---|
| Cl | 0.321 | 1 | | |
| ESP | 0.270 | 0.549 | 1 | |
| Na | 0.559 | 0.600 | 0.817 | 1 |
| Depth | 0.339 | 0.605 | 0.558 | 0.524 |

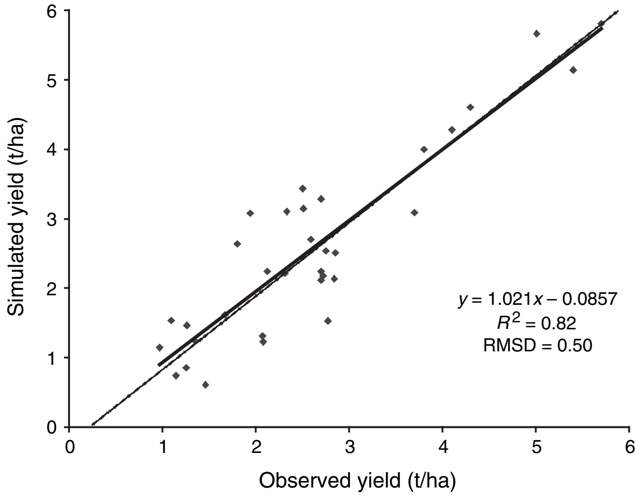


**Fig. 1.** Simulated and observed wheat yields at 33 sites with various levels of EC, Cl, exchangeable Na, and ESP in the north-eastern cropping zone, using CLL to account for the effect of the SSCs.

with SSCs indices (see Expt 2*b*) resulted in a modified depth function in which:

$$f_d = (DUL - LL_i) * (1.0 - [D_{par} e^{(Dmax-d)/(1.5-0.5)}]) \quad (3)$$

where Dmax = 1.5 m and $D_{par} = 0.39$.

Figure 2*b* shows that this function accounts for 66% of the observed variability in grain yield with a RMSD of 0.038. With this function the great majority of data lies on or below the 1 : 1 line. This provides an opportunity to develop functions based on each of the SSC indices and see if any of them improve the fit of observed and predicted CLL values.

### *(b) Modifying predicted $CLL_d$ values as a function of measured chemical SSC values*

To account for the effect of SSCs on CLL values, the $CLL_d$ values (using Eqn 3) were modified as a function of SSC indices using the generalised equation:

$$CLL_{SSC} = MIN\,(DUL, CLL_d + [(1.0 - \text{SSC Factor}) * (DUL - CLL_d)]) \quad (4)$$

and

$$\text{SSC Factor} = a * e^{b*\text{SSC}} \quad (5)$$

where the value of the SSC Factor is constrained to values between 0 and 1.0.

In order to evaluate the efficacy of the 4 indices of SSCs (EC, Cl, ESP, and Na), each of these was substituted for SSC in

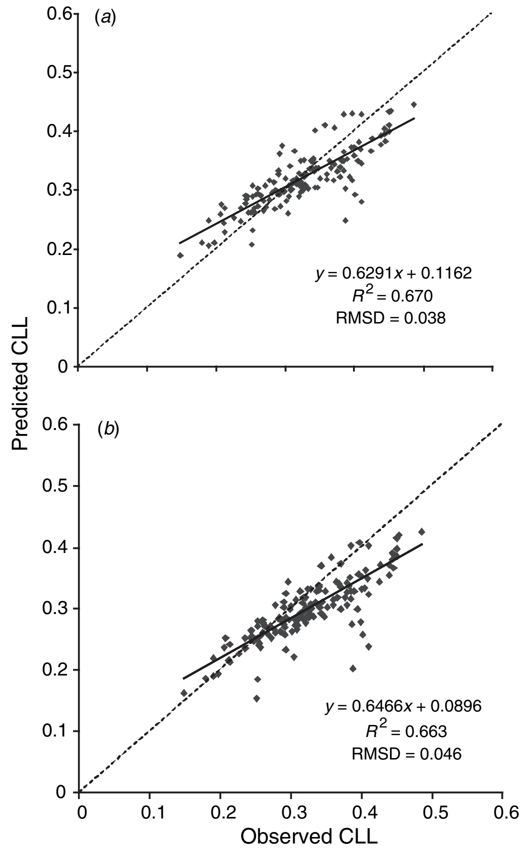


**Fig. 2.** A comparison of observed CLL with predicted CLL of 33 soils for layers between 0.5 and 1.5 m depth, when predicted CLL was limited only by soil depth and the function was either (*a*) optimised to minimise RMSD, or (*b*) optimised iteratively so that the effect of specific SSCs was separated from that of depth.

Eqns 4 and 5. The *a* and *b* parameter values that minimise the RMSD between the measured CLL values and the calculated $CLL_{SSC}$ values were derived for each of the SSC indices.

A comparison of the 4 SSC indices used to estimate the effect of SSCs on CLL (Table 3) shows that ESP is the most effective. While Na is marginally less effective than ESP, when compared with the EC and Cl based functions, the Na function produced a higher coefficient of determination and lower RMSD. Given that obtaining ESP values is significantly more costly than obtaining Na values, a cost-accuracy trade off might be usefully considered if such a function were used for guiding site-specific crop management.

Figure 3 shows the optimised function for ESP in which the differences between measured CLL and $CLL_{ESP}$ were minimised when $a = 1.7$ and $b = -0.04$. The exponential function had a threshold value of 13% while the concentration required for halving the difference between $CLL_d$ and DUL was 30.5%. These critical values compare with a mean value at 0.7–0.9 m of 22.0% for the 29 sites with ESP values in this study.

A comparison of the measured CLL values with the calculated $CLL_{ESP}$ values as determined above showed that this model accounted for 79% of the observed variability in CLL

**Table 3. Comparison of parameter values and efficacy of substituting EC, Cl, ESP, or Na for SSC in the generalised equation SSC Factor = $a * e^{b*SSC}$, used to modify $CLL_d$ to predict CLL values**

| | *a* | *b* | $R^2$ | RMSD |
|---|---|---|---|---|
| EC | 1.0 | −0.057 | 0.61 | 0.044 |
| Cl | 1.0 | −0.00055 | 0.69 | 0.037 |
| ESP | 1.7 | −0.04 | 0.79 | 0.032 |
| Na | 1.22 | −0.10 | 0.75 | 0.035 |

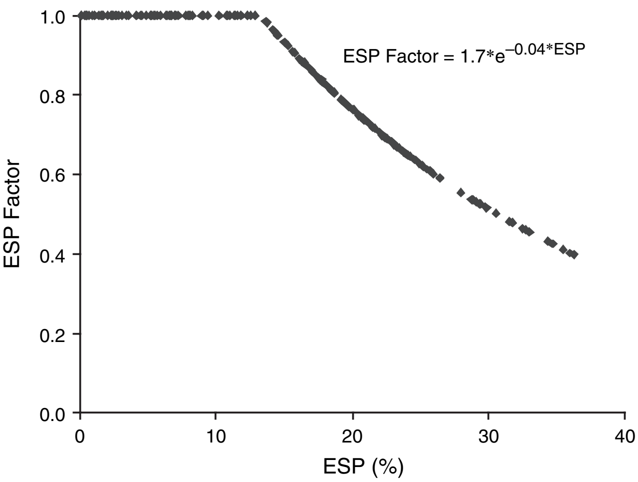


**Fig. 3.** Optimised factor for modifying CLL as a function of ESP.

with a RMSD of 0.032. A comparison of Fig. 2 with Fig. 4 shows the improvement obtained by using the ESP function. Predicted $CLL_{ESP}$ values had little systematic bias relative to the observed CLL values and the coefficient of determination was higher, indicating that ESP values provide a useful function for improving prediction of CLL for these soils.

### *Experiment 3: Replacing measured CLL with depth limited CLL and SSC modified kl values*

#### *(a) Determining depth limited CLL*

In this step a depth limited but non-SSC limited CLL value was calculated for each depth layer of each of the 33 soils. The depth modified CLL function was defined as:

$$CLL_d = CLL_{0.3–0.5} + f_d * d \tag{6}$$

where $CLL_{0.3–0.5}$ is the CLL measured at 0.3–0.5 m depth, $f_d$ is the depth parameter, and d is depth (mm) of the middle of the soil layer.

The optimal value determined for $f_d$ was 0.000045. Figure 5 shows the performance of the APSIM model when the measured CLL values of Expt 1 were replaced by the calculated $CLL_d$ values as determined above and no specific parameter was used to account for SSCs. This model accounted for 70% of the observed variability in grain yield with a RMSD of 0.78 t/ha. Compared with simulation using the measured CLL (Fig. 1), this function resulted in significantly lower correlation and a systematic tendency to over-predict grain yield. This result indicates the potential for improving yield prediction if

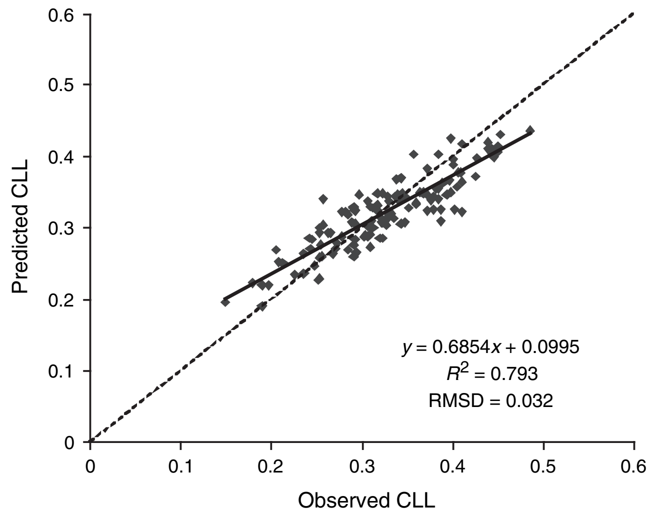


**Fig. 4.** A comparison of observed CLL with predicted CLL of 29 soils for layers between 0.5 and 1.5 m depth, when predicted CLL was limited by soil depth and soil ESP.

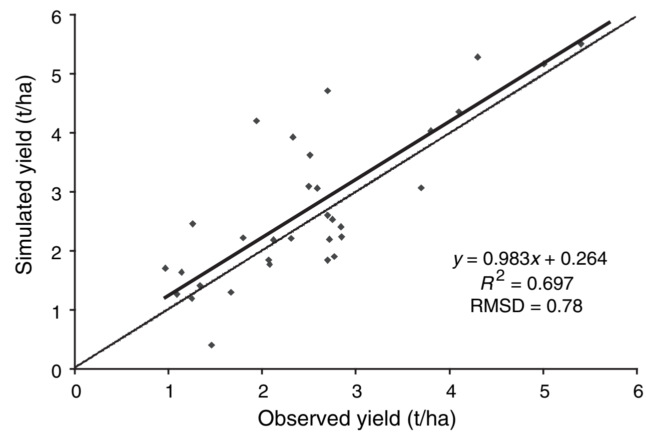


**Fig. 5.** Simulated and observed wheat yields at 33 sites with various levels of EC, Cl, exchangeable Na, and ESP in the north-eastern cropping zone, using the calculated $CLL_d$.

a suitable function can be developed to account for the effects of SSCs.

#### *(b) Replacing standard kl values with SSC limited kl values*

Here standard kl values were modified as a function of measured chemical SSC values using the equations:

$$Kl_{SSC} = kl * kl_{SSC}Factor \tag{7}$$

and

$$kl_{SSC}Factor = MIN\,(1.0, a * e^{b*SSC}) \tag{8}$$

In order to evaluate the efficacy of the chemical indices of SSCs (EC, Cl, and ESP), each of these was substituted for SSC in Eqns 7 and 8. The *a* and *b* parameter values that minimise the RMSD between measured and simulated grain yields were

**Table 4. Comparison of parameter values and efficacy of substituting EC, Cl, or ESP for SSC in the generalised equation SSC Factor = $a * e^{b*SSC}$, used to modify kl to predict grain yield values**

| | $a$ | $b$ | $R^2$ | RMSD |
|---|---|---|---|---|
| EC | 3.0 | −1.3 | 71 | 0.80 |
| Cl | 4.0 | −0.005 | 84 | 0.53 |
| ESP | 10.0 | −0.15 | 82 | 0.58 |

derived for each of the SSC indices. A comparison of the 3 SSC indices used to estimate the effect of SSCs on yield (Table 4) shows that Cl is the most effective index of SSCs.

Figure 6 shows the optimised $kl_{Cl}$Factor function in which $a = 4.0$ and $b = -0.005$. The exponential function has a threshold Cl value of 277 mg/kg and the concentration required for halving the kl value was 416 mg/kg. These critical values compare with a mean Cl value at the 0.7–0.9 m depth layer of 566 mg/kg for the 33 sites of this study. The 416 mg/kg threshold can also be considered in the context of 62% of Queensland's cropping zone of 2 450 000 ha having Cl >400 ppm at 0.7–0.9 m depth (Farquharson *et al*. 2006).

Table 4 shows that the EC data did not offer a useful modifier of kl for improving yield prediction. This finding is consistent with the observations of Dang *et al*. (2006*b*) that the presence of gypsum in some Vertosols of this region can confound the predictive value of EC as an index of SSC. The result of using ESP data to modify kl values was marginally less successful than of using Cl data. While either ESP or Cl measurement provides a satisfactory solution for improving yield prediction for soils with SSC, the measurement of Cl is cheaper.

Figure 7 shows the performance of the APSIM model in predicting grain yield with the depth limited CLL values of Fig. 5, but this time $kl_{Cl}$ values replaced the standard kl values. This model accounted for 84% of the observed variability in grain yield with a RMSD of 0.53 t/ha. Compared with the measured CLL (Fig. 1) there was little loss of correlation. Compared with Fig. 5 there was significant gain from substituting standard kl values with Cl related kl values. This result indicates that Cl data provide a useful modifier of kl for improving yield prediction for soils with SSC.

In addition to comparing the performance of the two approaches (measured CLL as per Expt 1 and the modified kl approach of Expt 3) with regards to grain yield, Fig. 8 provides a comparison of model performance with regards to simulated soil moisture of soil layers deeper than 0.5 m. Both methods simulate similar moisture values at anthesis as well as at grain maturity. While both correlations are quite good, the shift in data from tending to be above the 1 : 1 line in Fig. 8*a* to the opposite in Fig. 8*b* is not accidental and is a result of the different modes of rationing water use that are implied by the kl and the CLL methods. In the CLL method, water use in any depth layer is not restricted by the presence of SSCs until the crop approaches the CLL, while in the kl method, water use is rationed throughout the period in which the roots occupy the depth layer.

## Conclusions

Despite the different qualitative and quantitative attributes of soil chemical factors that are thought to be implicated in SSCs of soils in northern Australia, when compared with the attributes of subsoil constrained soils in southern Australia, the results of this study support and strengthen the conclusions from research in southern Australia that SSCs affect wheat crops primarily by increasing the CLL and thus reducing the PAWC. The imperative to reduce reliance on the measurement of CLL for every zone of management has resulted in two effective alternatives for simulating the effects of SSCs. The first method is based on the development of a depth and ESP dependent function for predicting the CLL of subsoils. The second method also uses a depth dependent function to reduce CLL but adds a Cl dependent function to modify the water extraction coefficient kl.

There does not seem to be a compelling explanation in the current dataset to account for Cl being the best predictor of yield when used to derive a modified kl function (Expt 3) but only marginally useful when used to derive a function to predict CLL (Expt 2). The most likely explanation lies in the different modes of rationing water use that are implied by the kl and the CLL methods. In the CLL method, water use in any depth layer is not restricted by the presence of Cl until the crop approaches the CLL, while in the kl method, water use is rationed throughout the period in which the roots occupy the depth layer. To determine which of these methods better explains the effects of Cl on the performance of wheat, it is necessary to

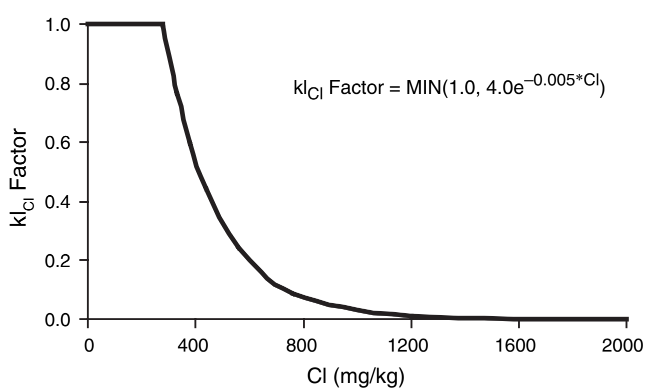


**Fig. 6.** Optimised factor for reducing kl as a function of Cl.

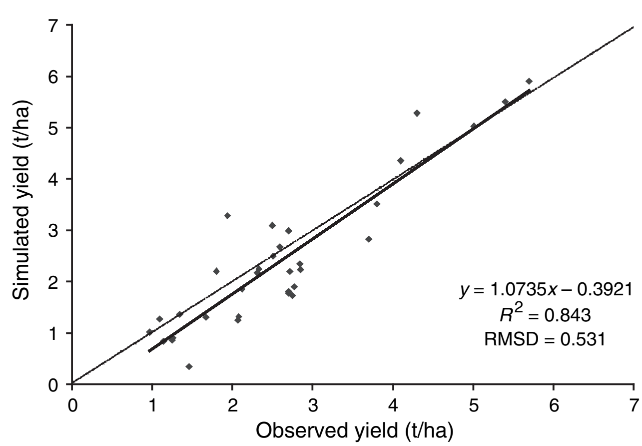


**Fig. 7.** Simulated and observed wheat yields at 33 sites in the north-eastern cropping zone using the calculated $CLL_d$ and $kl_{Cl}$ values.

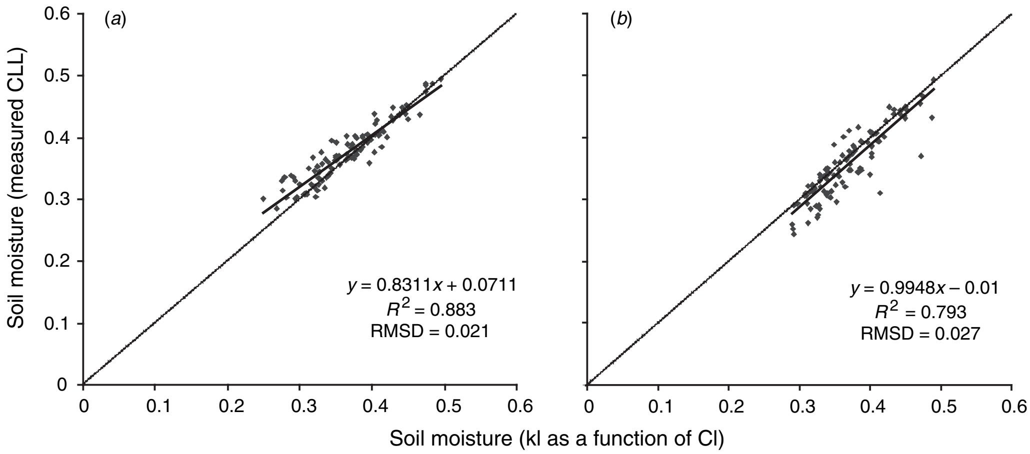


**Fig. 8.** Simulated soil moisture for layers deeper than 0.5 m, based on measured CLL compared with simulated soil moisture based on kl as a function of Cl at (*a*) anthesis and (*b*) grain maturity.

follow soil moisture extraction from the root zone throughout the season and observe which model predicts the water-use pattern more closely.

The results of this study provide a solid basis for use of simulation in extrapolating results of field experiments across locations and seasonal conditions. Simulation can now be used with confidence to explore the implications of SSCs on production and NRM issues and for exploring the likely efficacy of possible management adaptations to SSCs. In the context of zone-specific management, simulation studies of spatial and temporal variability of yield response to adjusting rates of nitrogenous fertiliser inputs could be used to develop regional/soil specific recommendations for best practice. Similarly, simulation could be used to investigate crop traits that are likely to be effective in combating SSCs. Traits that could be investigated include ones that improve the wheat crop's ability to explore and/or take up soil water in the presence of SSCs or, more simply, phenological traits such as early maturity that will help a crop avoid severe terminal droughts in some years.

The conclusions of this study apply to wheat crops grown on Vertosols in northern Australia. Further work is required to test the applicability of these findings to other crops and other soil types. Of particular interest is the study of species such as chickpea (*Cicer arietinum* L.), which are thought to be more sensitive than wheat to the presence of SSCs.

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