A tool for monitoring soil water using modelling, on-farm data, and mobile technology

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Abstract
Rainfall is low and unreliable in much of Australia's dryland cropping areas, requiring well-informed crop management for optimising yield and profit. Growing-season rainfall is usually supplemented by soil water during fallow periods preceding a crop. While rainfall is conveniently measured, the difficulty of measuring a soil's plant available water (PAW, mm) has led to using simulation models for estimating PAW. Here we developed a smartphone application (app) that simulates soil water balance by accessing weather, soil and crop data from databases and on-farm records. Predictions of PAW using the Howleaky modelling engine were compared with field measurements. Validation of the simulation engine across sites in Australian cropping areas showed good agreement between simulated and measured PAW. Errors in model estimates are compared with variability found within small fields. We conclude that estimating PAW for paddocks using a simulation model built in a smartphone app is a reliable and adaptable technology.

Keywords: Decision support, soil water, water balance, monitoring, modelling, app

1. Introduction

Crop production in Australian agriculture is limited by the water supply and water use efficiency (WUE, kg/ha/mm; French and Schulze 1984) of farming systems. Many dryland farmers are familiar with concepts of yield targets based on WUE which relates crop yield directly to water supply (water stored in the soil at planting plus in-crop rainfall). WUE is simple, transparent and well suited to communication with farmers. In a study of 334 commercial wheat crops, Hochman et al., (2009) found a WUE value of 15 kg/ha/mm and a threshold value of 67 mm. Nutritional disorders, pests and disease reduce yield below these guideline values of WUE and provide evidence of crop disorders (Cornish and Murray 1989). Nevertheless, the importance of water supply to dryland crops is overarching, as summarised by Routley (2010); "Water supply is clearly the factor most limiting the productivity and profitability … primary aim of dryland cropping systems … maximise the efficient capture, storage and use of this limited water." In the northern and drier areas of southern Australia there is insufficient rainfall during crop growth to achieve economically viable yields, so fallows are used to accumulate soil water to supplement in-crop rain. This dependency on water stored in a fallow varies from 5% in Western Australia to 60% in central Queensland (Thomas et al., 2007). The need for improved soil water management may increase in the future under a changing climate as climate adaptations are likely to have a greater reliance on stored soil water (Kirkegaard et al., 2014; Ghahramani et al., 2015).

Major investments in crop production occur at planting time and shortly after, when an uncertain water supply makes prediction of yield and financial return difficult. Financial losses from both under-investing and over-investing in crop inputs are common, but having a robust estimate of soil water at sowing time can reduce uncertainty (Thomas et al., 2007). Management options and farm financial risk profiles can be decided by soil moisture status of a paddock. A high potential yield attracts greater investment in crop establishment, nutrition (Moeller et al., 2009), crop protection and informs marketing decisions. On the other hand, low yield potential informs a variety of agronomic and business decisions with inputs often being reduced. Although predicting grain yield before or early in the growing season is challenging, applying the WUE framework to predict yield is well established (French and Shultz, 1984; Moore et al., 2011) and is improved by a reliable estimate of plant available water (PAW) near planting. PAW is water that is available to plants during the crop phase, is regarded as "safe" water as it is mostly immune to evaporation loses due to its depth of storage and sustains crops between rainfall events.

PAW is calculated for each soil layer from the difference between gravimetric water content (g g^{-1}) and the soils lower limit (LL or wilting point) and considering the thickness and bulk density of each soil (Lawrence et al., 2005). Plant available water capacity (PAWC) refers to a soil's capacity to store water and is often taken as a soil property, although it can be dependent on crop type. PAWC is calculated from a soil's LL and drained upper limit (DUL or field capacity) (Dalgliesh and Cawthray 2005). Estimating PAW and PAWC is expensive and labour-intensive.

In this paper, we explore errors in predicting soil water using a water balance model along with an analysis of spatial variability in relatively small fields. It is recognised that there are errors associated with instrument calibration and estimating basic soil properties such as bulk density and LL required in calculating PAW (Dalgliesh et al., 2009). Because of these errors and high spatial variability in field conditions, PAW is not a variable to be measured directly in a simple manner by farmers and consultants. Early simulation models of crop growth and yield were focused on predicting the supply of soil water with a view to managing crop water use and increasing WUE (e.g. Fitzpatrick and Nix 1969, Nix and Fitzpatrick 1969).

The capability to estimate PAW within soil and cropping systems models, such as Howleaky (McClymont et al., 2016) and Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014) is largely inaccessible to practical agronomists and farmers as those models were designed as research tools, not as information products. Decision support tools that do incorporate soil and crop dynamics such as Yield Prophet (https://www.yieldprophet.com.au) require considerable system specification whereas the app being introduced here aims to provide a robust and rapid estimate of soil water, aimed at farmers and consultants as users.

In developing a smartphone app to provide estimates of PAW to farmers and their consultants, it was considered prudent to understand the accuracy and reliability of a model based estimate of PAW. Confidence in the performance of models is usually obtained by comparison with field observations for the key variables of interest to the scientist, such as runoff, erosion and water quality (Knisel 1980; Williams 1983; Littleboy et al., 1992) or crop biomass and yield (Carberry et al., 2009), while it has largely been assumed that models accurately predict PAW. Such a narrow focus is expected as most components of the water balance are difficult to measure. For example, runoff is infrequent and unpredictable, making it difficult to maitain equipment (Freebairn et al., 1986), while deep drainage is technically difficult to measure and subject to high spatial variability (Humphreys et al., 2003). While evapotranspiration is more spatially homogeneous and accurately measured variable in a water balance analysis, calculations of the Bowen Ratio (Fritschen 1965) and related methods require advanced instrumentation, complex mathematics and are labour-intensive and expensive. These methods are almost exclusively applied where crops are growing, and water flux to the atmosphere is unable to be apportioned to soil evaporation and transpiration.

The analysis presented here was part of the design of a virtual soil water monitoring system, SoilWaterApp, which is aimed to meet farmer and adviser needs . We evaluate the water balance model in Howleaky (McClymont et al., 2016) used in SoilWaterApp to estimate changes in PAW. Also, we investigate the ability of a smartphone app to estimate the components of water balance from meteorological, soil and crop information, providing estimates of PAW for improved crop management through system design. SoilWaterApp is available from the Apple Store in Australia and documented at http://www.soilwaterapp.net.au. SoilWaterApp has some special features: fast simulation of the water balance on a smartphone or tablet; connection to climate, soil and crop databases; accept on-farm data; and sufficiently user-friendly to accommodate a wide range of users including farmers and consultants.

2. Water balance model

The water balance model used in the app has evolved from CREAMS (Knisel 1980) which predicted PAW, runoff and soil erosion from a combination of rainfall and evaporation data with (i) the runoff model of Williams and La Seur (1976), (ii) the soil evaporation model of Ritchie (1972) and (iii) the USLE for soil erosion (Williams 1983). CREAMS was influential in the development of PERFECT (Littleboy et al., 1992) and later Howleaky (McClymont et al., 2016). The latter model uses the Williams-Ritchie water balance model (Williams and La Seur 1976; Ritchie 1972) which is a one-dimensional mechanistic model, with parameterisation strongly based on a wide range of empirical studies (Littleboy et al., 1992; http://Howleaky.net/index.php/library). Simulation is performed on a daily time step. Surface runoff is estimated as a function of daily rainfall, soil water deficit, surface residue and crop cover. The model has a "cascading bucket" structure where infiltration is partitioned into soil layers from the surface, filling subsequent layers to total porosity. In the model, vertical water movement occurs if the layer is wetter than its field capacity and the layer below is drier than its field capacity. Water flux is limited by the saturated hydraulic conductivity of each layer. Soil water can be removed from the profile by transpiration, soil evaporation and downwards movement from the lowest layer as deep drainage. Transpiration is a function of pan evaporation (a climate input), leaf area or percentage green cover and soil moisture. Soil evaporation removes soil water from the upper two layers. The sum of transpiration and soil evaporation (evapotranspiration) cannot exceed pan evaporation on any day. A summary of the soil water balance model in Howleaky is presented in the supplementary material S1.

3. Architecture: Software and Data

SoilWaterApp has been developed for iOS devices using Apple's native Objective-C framework and communicates with a central cloud-based server for synchronising both app and user data. Operating the app involves setting up and monitoring a range of "sites" with different agro-climatic variables. Selecting a site in the user-interface will present an "analysis page" which automatically updates the soil-water results for the latest climate conditions using the HowLeaky model. During this process, it will update any outdated climate data and provides the user with a range of input and output infographics that progressively disclose more detail as the user scrolls down (Fig 1). Inputs are presented at the top of the analysis page and are grouped into soil, starting conditions, fallow/crop conditions, irrigation, local rainfall and soil-water sensor options. Outputs include a summary of predicted PAW; a time-series of recent, historical (past years) and predicted plumes of soil-water, recent stubble and crop cover; a soil-moisture profile graph; and a water-balance summary table.

(a) (b) (c)

Fig 1. Example of SoilWaterApp's user-interface showing (as user scrolls down the page): (a) input options and summary output; (b) soil-water and cover time-series; and (c) soil-moisture profile and water-balance table.

The App has been developed with a multithreaded design for parallel processing of data input, output and analysis streams. It is composed of a range of independent functional modules for data input, storage and synchronisation and for running soil-water analyses using the *HowLeaky Engine*. Figure 2 shows these modules and how they interact with each other and external data sources. Database operations are handled by a *CoreData Manager* module and multiple synchronised database instances known as “managed object contexts”. Separate “contexts” ensure that data integrity is maintained during asynchronous operations of the *Data Synchronisation Manager*, *Bluetooth Manager* and running of the *HowLeaky Engine*. Temporary *View-Models* are used to safely transfer data between the *CoreData Manager* and *HowLeaky Engine* and to provide an “undo” and “redo” functionality for user-settings changes. A *Climate Data Manager* module facilitates updating local climate data from the SILO data server (https://www.longpaddock.qld.gov.au/silo/) while an *Export Manager* module allows analysis data and results to be shared with other users. The app communicates with several external Application Programming Interfaces (APIs), including a cloud-based database, a climate data provider and Bluetooth rain-gauge and soil water sensors.

Key to the software’s operation is a *Data Synchronisation Manager* which synchronises both application and user data between multiple mobile devices and a server. Data includes soil and vegetation descriptions, climate locations, project, site and simulation data and analytics to track the app’s use. This allows data to be collected on one device (with or without an internet connection) and synchronised with the SoilWaterApp “server” and other mobile devices once an internet connection exists. It operates in different modes including “one-way from the server to device”, “two-way between server and device” and “one-way between device and server” depending on the nature of the data.

SoilWaterApp relies on a range of short and long-term time-series data that are retrieved and stored using different methodologies. Long-term records of daily historical climate data from the SILO “patched point” database (Jeffrey et al 2001, www.longpaddock.qld.gov.au/silo/) are stored locally as ASCII files on the user’s device and automatically appended to each time the app is active. These files are replaced after two weeks as the SILO data files are prone to data-corrections over time. Users’ local short-term data such as “rain-gauge”, “soil water sensor” and “irrigation” data are stored in the database in records spanning three-monthly “data chunks” to facilitate efficient retrieval and synchronisation between device and server.

4. Model evaluation

Performance of the water balance model in SoilWaterApp was evaluated for three data types: fallows with detailed long-term observation of gravimetric soil water collected from hydraulically driven soil cores (three sets of small catchments); daily data for a sequence of fallow and crops at two sites using capacitance probes; and a set of BlueTooth enabled Decagon soil water sensors and a rain gauge integrated with the SoilWaterApp. Comparisons between soil water observations and model estimates were carried out using the Howleaky model (McClymont et al 2016) as this was the most efficient process and the app is not suited to model testing. The model in the app and Howleaky were verified to produce identical outputs when given the same inputs.

4.1 Fallow

In Australian dryland cropping systems, fallows are instigated to store soil water, accumulate soil nitrate and control weeds in preparation for the next crop to reduce the risk of failure and increase yield, especially where soils have a high water holding capacity. Field observations of fallow effect on soil water were available from three long-term experimental sites in the state of Queensland (Greenmount, 27°44'27"S 151°51'33"E; Greenwood, 27°19'42"S 151°43'47"E; Wallumbilla, 26°34'28"S 149°11'17"E) where the focus of each study was to better understand the role of tillage and stubble management on moisture and soil conservation (Freebairn and Wockner 1986; Freebairn et al., 2009). Rainfall, runoff and soil water were monitored over periods of 7-17 years equivalent to ~170 plot-years of data with each plot being sampled at least three times each year (start, mid and end of each fallow period). Each soil sampling consisted of nine soil cores

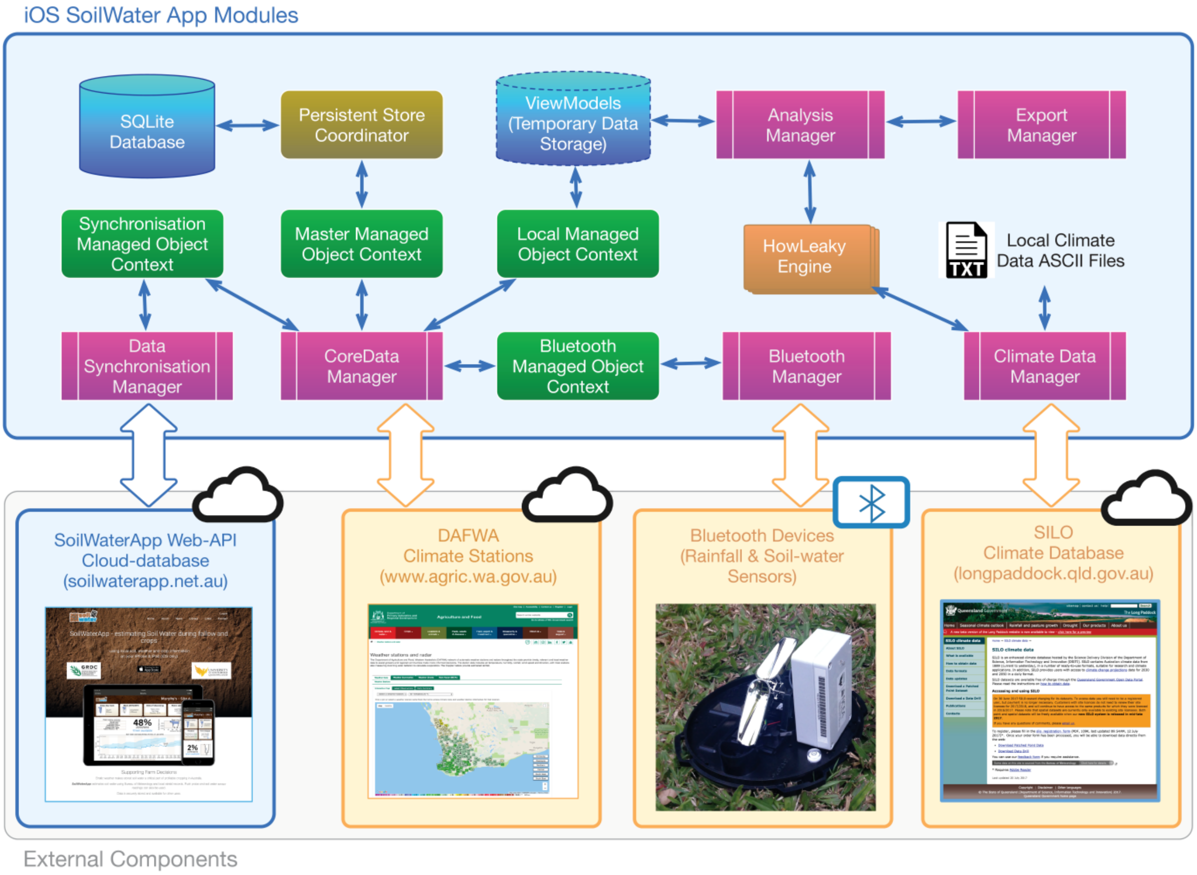

Fig 2. A schematic of SoilWaterApp's software structure

taken in each bounded catchment (referred to hereafter as a "bay") at 0-10, 10-30, 30-60, 60-90, 90-120 and 120-150 cm depths (see Fig 3a for sampling patterns). Plant available water (PAW, mm) was estimated from a field-measured lower limit (LL, cm^3/g) (Dalgliesh and Foale, 1998) and measured soil bulk density (g/cm^3) and is presented in this paper as an average of total profile PAW for each sample date. Field experiments were conducted under two common but contrasting soil management conditions; stubble burnt after harvest with little soil cover and zero-tillage with 30-80% cover from crop residue. Measured and predicted change in PAW between sample dates is used rather than absolute values of PAW to reduce artificial skill in the statistics. All related weather, agronomy practice and soil descriptions, and soil water data are accessible from a database of experimental sites focusing on water balance and water quality across Australia (http://howleaky.net/index.php/library).

4.2 Fallow and crops

SoilWaterApp's modelling engine was evaluated for its ability to simulate PAW in crop-fallow sequences at two sites in the state of the Victoria: Youanmite (-36.1639°S, 145.6640°W) and Hamilton (-37.7277°S, 141.9242°W). Each site had one sample location with 8 capacitance sensors at 30, 40, 50, 60, 70, 80, 90 and 100cm depths (EnviroPro® EP100G-08, Entelechy Pty Ltd, Adelaide, Australia). The shallow sample was located to avoid damage by tillage equipment and was sited to avoid wheel tracks. The surface 25 cm was not sample. While these data are more limited in terms of duration and fallow management practices, the daily time series provides more detail on soil water dynamics using measuring equipment similar to that increasingly being installed by farmers and consultants. In essence, this level of detail is a useful benchmark for evaluating SoilWaterApp's ability to track soil water dynamics at a daily time step.

4.3 Surface water dynamics

SoilWaterApp accepts data directly from a BlueTooth enabled data logger connected to a tipping bucket rain gauge and three Decagon Devices, Inc. 10HS soil water sensors. To test a prototype system, we installed a sensor/logger system into a bare soil plot at the University of Southern Queensland, Toowoomba (27°36'52.0"S 151°56'14"E). Daily rainfall and soil water content were recorded from June to October 2016 (20 weeks). In this experiment, the surface 10 cm of soil was monitored at 4 cm, 6 cm and 8 cm, representing a measurement zone of 0-5cm, 5-7cm and 7-10cm respectively, with a focus on testing the evaporation algorithm within SoilWaterApp as well as the robustness of deploying the system into a field setting. The soil description reflected the sensed layers for a shallow Ferrosol.

5. Spatial variability in field measurements

Plant Available Water Capacity (PAWC) is often taken as a soil property and is an important descriptor used in biophysical models. We explored the spatial variability in measurements from three long-term datasets (also used in section 4.1) that represent cropping in southern Queensland (available at http://Howleaky.net/index.php/library). A soil survey with detailed pedology and chemical assessment did not reveal any marked differences in soil type across a 12ha site, with soil depth > 2m across the three sites (i.e. soil depth should not be limiting to plant growth). At Greenmount and Greenwood, distance between sample areas is relatively short (50-60m). Greater variability would be expected at Wallumbilla as it was a larger site, with sample sites ~150m distance apart on a diverging slope. Samples displayed greater variation in colour when sampled. All three study sites represent areas < 10% of a normal "paddock" in their respective regions.

6. Operating the App

Daily rainfall and evaporation data from SILO are accessed by SoilWaterApp via mobile telephone or Wi-Fi networks. Once a site is established (climate, soil type, cover and crop dates) taking a new user <5 minutes, soil water estimates are immediately updated using weather data up to the day before (yesterday) each time the app is opened. Multiple sites can be established and shared between users. Given the high spatial variability of rainfall and sparse network of gauges in some parts of grain growing regions, users can enter local rainfall data manually or use an automated rain gauge that connects to the mobile device via Bluetooth Low-Energy (BLE). In addition to the BLE rain gauge, a small number of BLE data loggers have been deployed with soil moisture sensors to monitor PAW daily. Whenever the user is within BLE range (< 20 metres), a seamless communication and transfer of the soil water and rainfall data from the logger to the app occurs. The app and its associated API includes databases of soil parameters for estimating daily runoff, deep drainage, soil evaporation, and PAWC. Similarly, a database of crop parameters describing green cover and root depth distributions is required for estimating transpiration and soil water extraction. Crop residue cover, used to modify infiltration and evaporation, is specified by the user. Databases are updated with app use while a system administrator can easily manage the 'reference' databases of soil and vegetation descriptions.

7. Results and discussions

7.1 Modelling capability of the app

The performance of the app's modelling engine in simulating changes in PAW over fallows and crops for a range of rain-fed agricultural systems is evaluated. Fig 3a presents a comparison of simulated and observed gains in PAW for the three long-term field studies in the state of Queensland (Greenmount, Greenwood, and Wallumbilla). There was agreement between simulated and observed values for each practice and soil type. The scatter of measured and observed data in Fig 3a has a range of R^2 values from 0.72-0.76 across sites and treatments, with an overall R^2 of 0.69 indicating reasonable confidence in model estimates across multiple seasons, soil types and fallow management conditions. Regression analyses were carried out using MS Excel statistics.

The pattern of error shown in Fig 3a frequently occurs in models of this type due to inadequate representation of biological and physical processes that give rise to low and high values. For example, regression of observed and APSIM predictions in 15 studies of crop yields resulted in low slope (< 1) in 12 studies and a high intercept (> 0) in 13 of those studies (Carberry et al., 2009).

At Youanmite (State of Victoria), daily values of observed and predicted PAW are in step during the crop of 2015 that was planted with low PAW and subsequently suffered severe water stress (Fig 3b). The disagreement between simulated and measured replenishment of PAW over the summer fallow where Howleaky overestimated PAW accumulation may be attributed to errors in parameters describing surface soil water characteristics or missing rainfall data. The flat sections in model estimates are an artefact of soil water data being available for 30-100cm layers as sensors were buried beneath the tillage depth. Plotted model estimates ignored layer 1 (0-20cm), therefore not showing soil surface water dynamics. PAW predictions in June and July are in agreement with measurements, an important outcome given the app is used to guide inputs during early crop growth.

Results from the Hamilton site show good agreement between observations and estimates of PAW with both accumulation and depletion of PAW predicted well (Fig 3b). These comparisons lead to confidence in predicting gains in PAW during fallows with small and generally explainable errors during periods of crop water use. An analysis of errors found that unreliable rainfall data and poor specification of soil constraints accounted for most poor predictions of PAW. Unreliable rainfall data came from poorly maintained digital rain gauges. It is recognised that field data collection is challenging given environmental extremes while soil specification remains a challenge for site-specific applications of models.

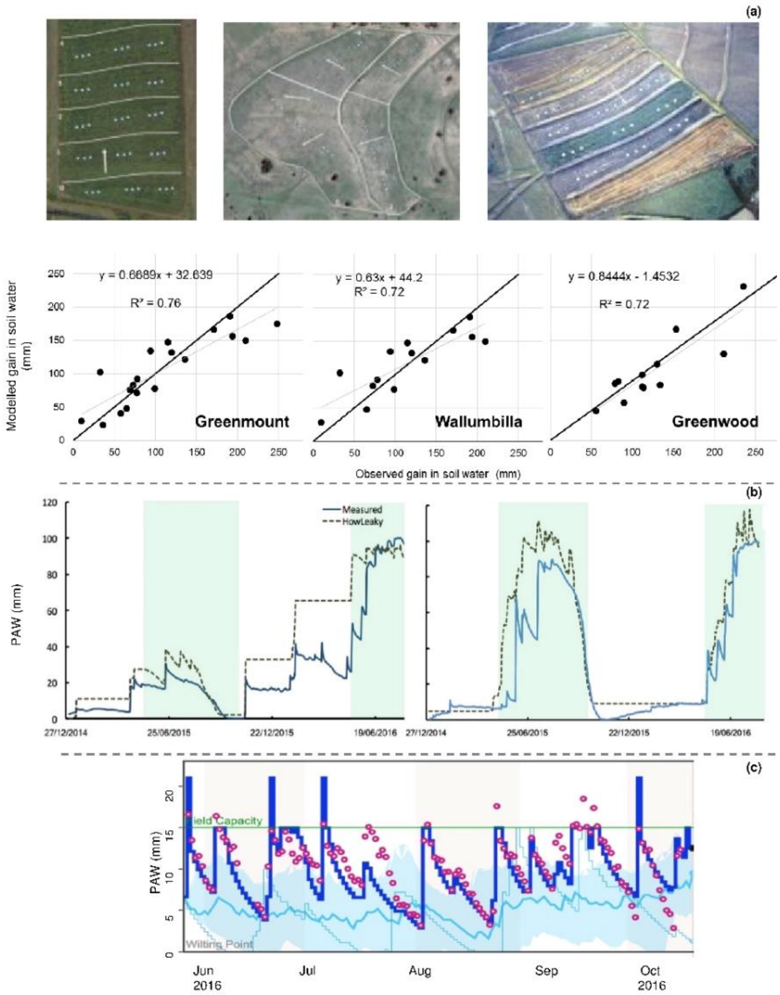

Fig 3 Modelling capability of the app across six contrasting sites (a) Aerial photographs of the Greenmount (left), Wallumbilla (centre), and Greenwood (right) field studies showing soil sample patterns - the distance between sample “triples” is ~50m at Greenmount, 150m at Wallumbilla and 40m at Greenwood. Arrow indicates direction of slope. Observed and predicted gains in soil water are shown below each photograph with root mean square error (RMSE): Greenmount = 30mm; Greenwood = 27mm; Wallumbilla = 34mm. (b) Daily observations and predictions of PAW (mm) (20-100cm soil layers) at Youanmite (left) and Hamilton (right) from late 2014 to mid-2016. Green shading indicates crop period. (c) Screenshot of SoilWaterApp’s time series of estimated soil water (dark blue line) and PAW (plant available water) estimated from Decagon moisture probes (red dots). Rainfall and soil water data were collected from a data logger using BLE communication directly to the app. The heavy light blue line indicates average PAW, the thin blue line-last year’s estimate while the blue plume indicates 60% of previous years. Wilting Point and Field Capacity refer to the lower and upper limits of PAW in the soil profile

Fig 3c shows PAW estimated by SoilWaterApp and measured values derived from capacitance sensors, demonstrating linking local rainfall and soil water data with the ability to customise a soil type for a site. Fig 3c shows that when SoilWaterApp is suitably configured, its water balance simulation and field sensors provided comparable estimates of soil water in a simple experiment focusing on evaporation losses. This combination of sensors, a Bluetooth logger and SoilWaterApp is a valuable development in bringing a simple and reliable soil water sensing system and modelling to soil scientists, agronomists and eventually farmers. While this system is not commercially available, Fig 3c displays the system’s simplicity, low cost, accuracy without calibration and direct link between a monitoring device and a water balance simulation.

7.2 Why a virtual soil water monitoring tool?

To compare field variability of soil water observations with errors associated with modelling soil water, individual soil core data from the Wallumbilla study were analysed in detail for several sample dates. At the studies initiation, the site was chosen to be representative of a major soil type of the region and to be relatively uniform across the site, yet Fig 4a shows variability in PAWC (180-280mm) for four adjacent catchments over a 15 ha site (see Fig 3a). PAWC is regarded an important soil descriptor in water balance models and is important in calibrating soil sensors.

Figure 4b shows the variability in measured PAW for nine sites within a 3 ha bay for a sample date at the end of a summer fallow. While nine samples were collected with the aim of providing a robust estimate of PAW and changes in PAW for the 3 ha catchment, it is clear that reliance on a different number of sample locations would produce a different result. The standard deviation of gravimetric soil water for any depth is 1-2% which translates into a standard deviation of ~50mm of PAW. An outcome from these observations might be that users of models might have a more realistic view regarding specification of a model given the natural variability within a small area.

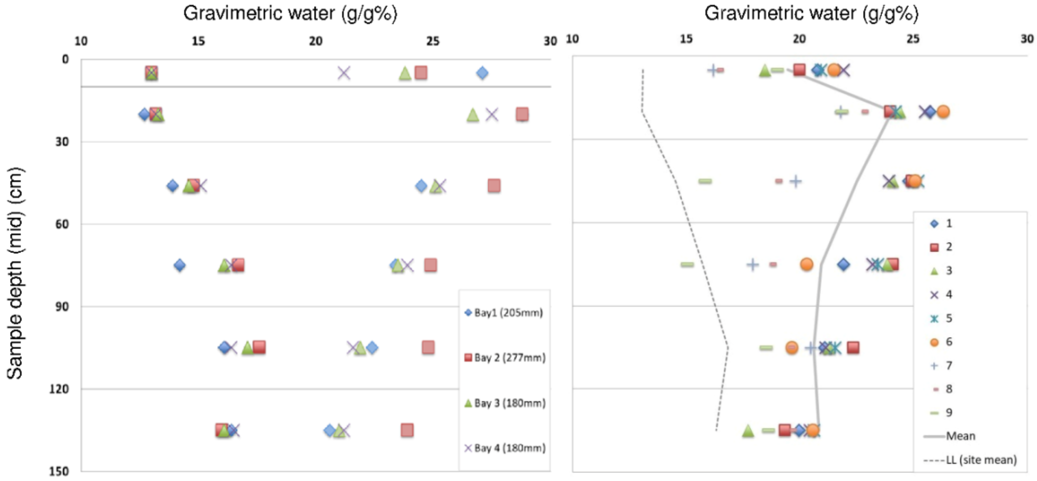

Fig 4 Gravimetric soil moisture at Wallumbilla showing (a) driest (left) and wettest (right) soil water content values (mean of nine samples) and PAWC (plant available water) for four adjacent bays of ~3ha and (b) gravimetric soil moisture for nine cores within Bay 3 for a soil samples collected towards the end of a fallow (25/5/98). The lower limit (LL) and mean for the sample are also shown. Bay is a bounded catchment as explained in trhe section 4.1.

These results, from an intensively sampled experiment over 17 years demonstrate that even in sites selected for their apparent uniformity, it is difficult to assume reliable values of soil lower limit (LL or wilting point), drained upper limit (DUL or field capacity) and consequent PAWC, even if errors in estimating soil bulk density are ignored. It follows that when soil water monitoring equipment is installed, that site selection will be challenging as the single sample site might be any one of the points on Figs 4a or 4b.

It is worth putting all these estimates of soil water into a context with where they may be used by decision makers. For example, farmers estimate PAW in numerous ways: intuition, from rainfall records and simple rules (e.g. a percentage of rainfall stored), steel push probes to detect the depth of moist soil, observation of crops, weather and soil water monitoring systems, and models (and apps) such as presented here. Table 1 lists some strengths and weaknesses of six methods of estimating PAW. Each approach has a fit in the real world of decision making for farmers.

Putting a financial value estimates of soil water regardless of method, is a challenge, dependent on enterprise, decision makers' attitude to risk and application of information to the decision-making process, and won't be attempted here. Nevertheless, a simple cost comparison of two contrasting approaches to tracking soil water: application of SoilWaterApp; and the installation of a commercial weather and soil monitoring station is presented. While the cost of developing SoilWaterApp was considerable (AUD$500,000), this cost can be spread over many users with minimal ongoing costs. A weather station with soil water sensors may cost AUD$2-10,000 per installation. Based on this simple cost model, when the app is used for > 250 sites, the cost per site will be less than a physical installation. SoilWaterApp has 2000 active sites being monitored 18 months after its release. More detail is presented in supplementary materials S2.

Approach	Strengths	Weaknesses	Cost
Intuition, rainfall records, fallow efficiency (default)	Decision maker experience, fast and no cost	Qualitative, biased by recent events, no information on water at depth	Nil, part of normal activity
Push probes	Fast, low cost, suited to clay soils, requires site visit	Biased, not suited to hard setting soils, requires site visit	Minor, site visits
Crop observation	Direct link to crop, integrated assessment	Observation may be too late to be useful	Site visits
Monitoring equipment (soil and weather)	Real-time, quantitative, visual (dashboard), rain and SW linked, remote access	May require calibration, small sample volume, high capital and moderate operating costs, prone to mechanical failure	$2-10,000/site
Water balance model or app	Real-time, quantitative, no or little cost, multiple sites no extra cost, remote access (optional), use range of rain inputs	Not a measurement (virtual), credibility, may be prone to mechanical failure	<$600/site/year
Spatial mapping of modelled soil water	Monthly, qualitative, low cost, remote sensing, suited to "big picture" clients	Not paddock or management specific	Nil for farmer

Table 1 Strengths and weaknesses of six approaches to assessing soil water status

7.3 Adoption of SoilWaterApp to date

While no formal evaluation of SoilWaterApp has been completed, Fig 5 shows locations and accesses in the first 18 months since SoilWaterApp's release. SoilWaterApp is being applied across Australia's grain growing regions where the importance of soil water status is well recognised. This initial adoption rate sets the scene for more in-depth assessment of the value of PAW (plant available water) estimates for grain growers. It is noteworthy that the top 200 users (by a number of sites) comprise ~80% of the total sites to date. Many of these users are consultants who are monitoring multiple sites.

8. Conclusions

We conclude that SoilWaterApp's modelling engine can reliably estimate patterns of PAW through fallows and crops and that an app is a practical approach to bringing climate, weather, soil, and crop information together for farmers and consultants to estimate PAW in their decision making. Simulation-based estimates of PAW are shown to be reliable and less expensive than physical measurements. An app-based estimate of PAW is well suited to application across multiple paddocks and soil types. Model-based estimates of soil water are reliable, easy to access in a mobile device app.

9. Acknowledgement

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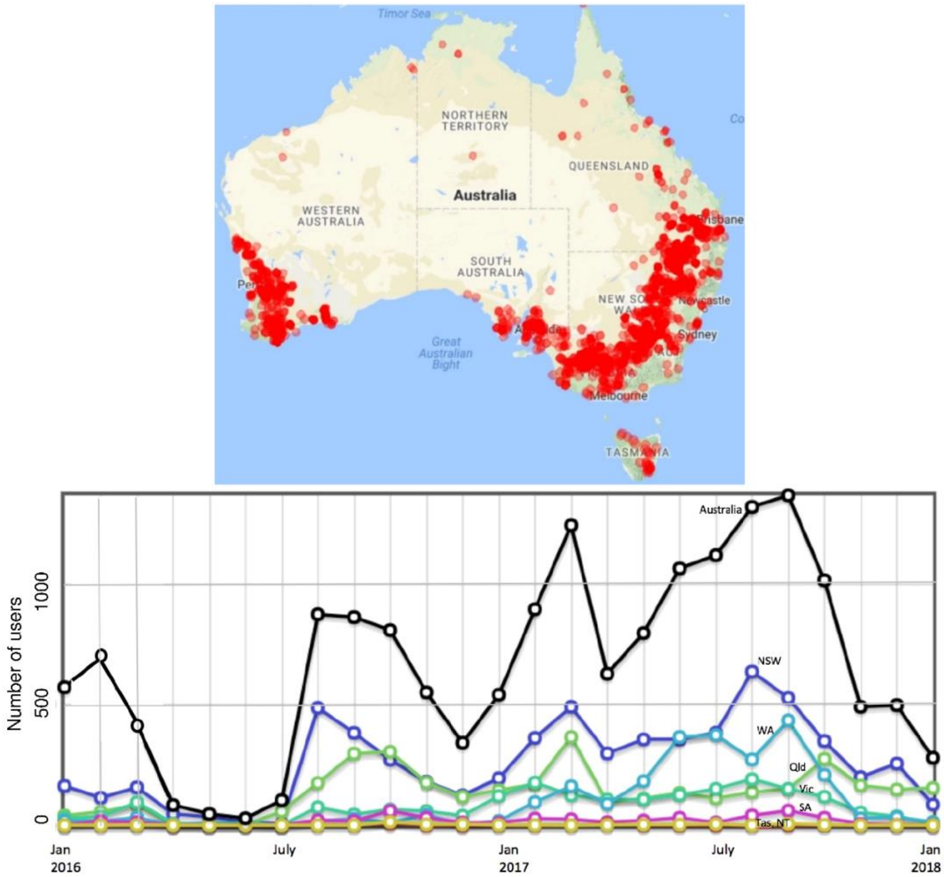

Fig 5. Distribution of sites (n=1960) and time series of sessions/month (n=16,600) for SoilWaterApp users since release (January 2016 to Jan 2018).

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