Environmental Modelling & Software 104 (2018) 55–63

Contents lists available at ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

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

D.M. Freebairn [a, *], A. Ghahramani [b], J.B. Robinson [a], D.J. McClymont [c]

[a] University of Southern Queensland, National Centre for Engineering in Agriculture, Toowoomba, QLD, 4350, Australia
[b] University of Southern Queensland, Institute for Agriculture and the Environment, Toowoomba, QLD, 4350, Australia
[c] DHM Environmental Software Engineering Pty Ltd, Toowoomba, QLD, 4350, Australia

A R T I C L E I N F O

Article history:
Received 30 November 2017
Received in revised form
30 January 2018
Accepted 15 March 2018

Keywords:
Decision support
Soil water
Water balance
Monitoring
Modelling
App

A B S T R A C T

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.

1. Introduction

Crop production in Australian agriculture is limited by the water supply and water use efficiency (WUE, kg/ha/mm; French and Schultz, 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 Schultz, 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

* Corresponding author.

https://doi.org/10.1016/j.envsoft.2018.03.010
1364-8152/

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 LaSeur (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 LaSeur, 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.

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*. Fig. 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