Soil water status and water table modelling using EM surveys for precision irrigation scheduling

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Abstract

Electromagnetic (EM) surveys have been used to quantify soil variability with respect to soil water storage in an irrigated maize field. A fluctuating water table (WT) sub-irrigates the crop in some places, and a wireless sensor network monitors real-time WT height and soil moisture, with large differences in soil moisture measured at any one time in these uniformly textured sands. Results indicate that EM38 survey data plus rainfall can be used to predict soil moisture (R^2adj = 0.87) and height of WT (R^2adj = 0.71) at this site, using a SAGA Wetness Index extracted from the digital elevation data.

Keywords: EM31, EM38, SAGA wetness index, water table, precision irrigation

Introduction

Productivity gains in global food supply have increasingly relied on expansion of irrigation schemes over recent decades. Simultaneously there has been a realisation that freshwater resources must be used at a sustainable rate, and that this can be partially addressed by improving irrigation water-use efficiency. Our research is trialling the benefits of modifying an existing sprinkler irrigation system with variable rate control of individual sprinklers, so that irrigation can be optimised according to soil water storage differences, at a resolution of about ten metres. This addresses the fact that the soil resource is a dynamic freshwater reservoir and its ability to store and supply plant available water varies temporally and spatially across the landscape.

High resolution quantification of the soil resource for precision management is enabled using EM (electromagnetic induction) surveys with geostatistical interpolation and ground-truthing of the datasets (Adamchuk et al., 2004). This geostatistical form of digital soil mapping acknowledges the importance of position in empirical descriptions of relationships of the soil resource to its environs (McBratney et al., 2003).

EM38 and EM31 surveys can be related to subsurface soil properties such as texture, moisture and depth to WT, and are used to define management classes for precision management (Triantifilis et al., 2009). Accurate elevation data collected during the survey provides opportunity to investigate the contribution of terrain attributes [microtopography] by analysis of the contour plot, which can then be co-related with EM data to improve these predictions. The most basic and commonly used primary terrain attributes include surface derivatives such as slope, aspect, and curvature. Secondary terrain attributes are calculated from a combination of two or more primary attributes, the most commonly used being the ‘topographic wetness index’ (TWI). The SAGA Wetness index (SWI) is similar to TWI but is based on a modified catchment area calculation, providing more sensitive predictions in landscapes with a small vertical distance to a channel (Boehner et al., 2002). The SWI therefore has potential to be more useful for precision management applications than the TWI which is most appropriate for wider hydrological studies.

The aim of this paper is (1) to present our progress developing a method to predict soil water status from digital EM survey data and elevation derivatives and, (2) to test this method using hourly updated soil moisture and WT data, obtained from a wireless soil moisture sensor network (WSN) installed under the irrigator.

Materials and methods

The field research site is a 75 ha maize field, irrigated by a centre pivot irrigator with variable rate (VRI) modification. The undulating sandy soils are influenced by a high and fluctuating WT, so that some areas of the field remain wet in Spring, delaying cultivation, while other zones dry out very rapidly and require frequent irrigation to avoid becoming hydrophobic for the remaining summer season.

Geonics EM38Mk2 and EM31 surveys were conducted in October 2010. A WSN was then installed into the research site, positioning nine nodes to monitor the full range of soils identified by the EM surveys. Sensors were attached at each node to monitor soil moisture and WT height, with data immediately made available over the internet through a web-based database in the gateway.

The Geostatistical Analyst toolbox for ArcGIS (ESRI®, 2010) was used to develop best variogram models (lowest RMSE) and for kriging. Terrain attributes were then extracted from the digital elevation map in SAGA (System for Automated Geoscientific Analyses) software, including a SAGA wetness index (SWI). Other data processing tasks have been undertaken using the R 2.12.1 statistical environment (R Development Core team, 2011).

Soil available water-holding capacity (AWC) and texture was assessed on intact soil cores collected from 3 depths (0-20cm, 20-40cm, 40-60cm) [3 replicates] from each of three classes (high, medium, low EM) derived from the EM38 survey data using ArcGIS (ESRI®, 2010).

Multiple linear regression models were used to investigate how well EM38, EM31, digital elevation and rainfall data could predict soil moisture and WT height, which were recorded hourly at each WSN node. Three predictors have been selected to dynamically model the WT depth: EM38, SWI and rainfall [EM38 and SWI have been log-transformed to overcome skewness of the data]. The rainfall data have been integrated over three days to account for the time required for the rain event to fully affect WT height. WT height, EM38 and SWI [the latter two being log-transformed] were then used to predict volumetric soil moisture content at 0.5 m.

Results and Discussion

Ground-truthing of the EM38 map shows large differences between AWC (range: 0.08±0.02 – 0.20±0.02) despite small differences in soil texture (percent sand range: 90 – 96%). The WSN also tracked large differences in soil moisture at any one time within this study area (Figure 1), reflecting the contrasting soil moisture release and available soil storage characteristics, and distance from WT. The WSN data (Figure 1) provides a dataset with limited spatial point data (n=9), reiterated hourly, providing opportunity to assess how prediction models vary with time and soil moisture status during the irrigation season. The multiple linear regression model satisfactorily predicted daily WT height from EM38, SWI and rainfall for a one month period (adjusted R^2 = 0.71). Daily predicted vs. measured plots for soil moisture content are presented in Figure 2. The overall performance of this model is very good (adjusted $R^2 = 0.87$), although a 66 mm rainfall event during the last days of monitoring decreases the model's performance.

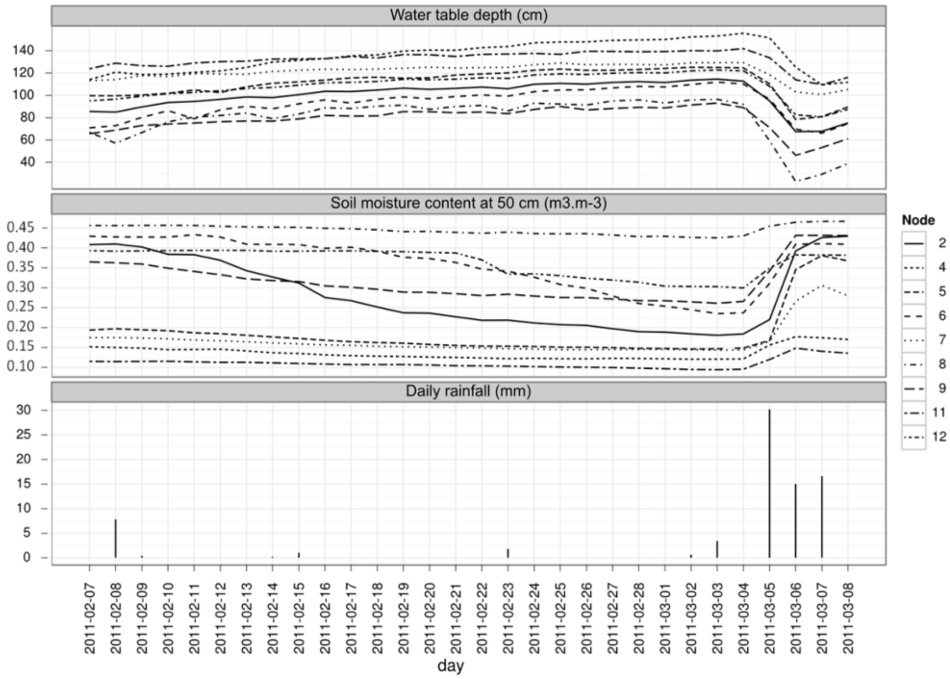

Figure 1. WT fluctuation, soil moisture (m^3m^{-3}) at 50 cm soil depth, and rainfall for the period 7 February – 7 March 2011.

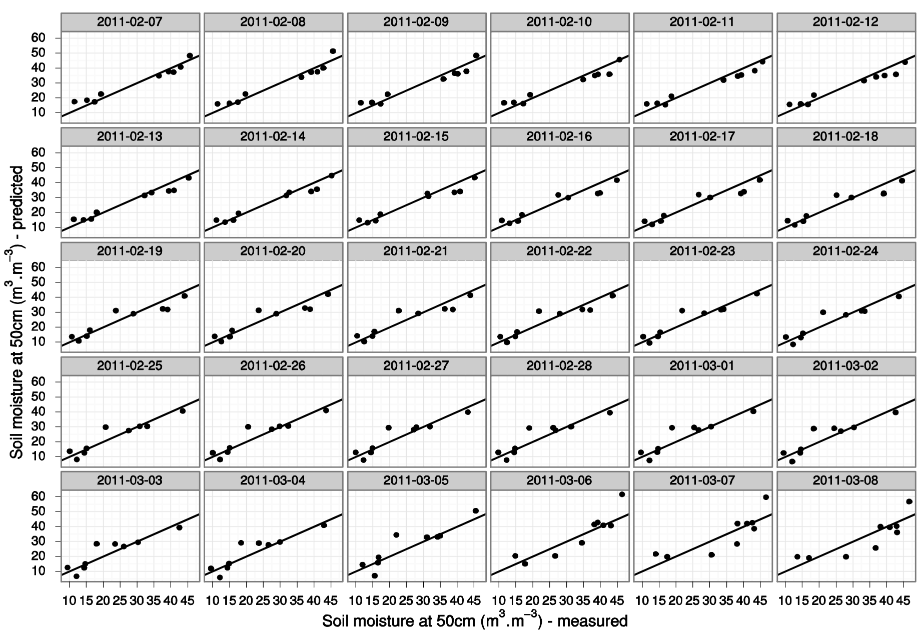

Figure 2. Predicted vs measured soil moisture content at 50 cm (m^3m^{-3} x10^2) for each day of monitoring

Results show that, at this site, where the WT occurred within 1.5 m of the soil surface, the height of WT is best predicted by EM38, and the EM31 data did not improve the prediction. Soil moisture is strongly influenced by fluctuating levels of WT, which illustrates the need to incorporate the contribution of sub-irrigation from high WTs into soil water balance modelling, if this is the method used to assist irrigation scheduling. However, the use of WSNs negates the need for soil water balance models because they can simultaneously monitor volumetric soil moisture and soil matric potential at each node providing real-time measurement of plant available water. In addition the relation of this soil moisture data to EM, DEM and rainfall data provides a method of spatial modelling of soil water status in real-time.

Conclusions

Precision irrigation scheduling requires regularly updated spatial knowledge of soil water status that can be supplied by a WSN. Through a simple modelling exercise, this study demonstrated that EM38 survey data can be used with rainfall as a basis to dynamically predict soil moisture and WT. This provides a method to translate WSN point data into daily updated soil water status maps for variable rate irrigation scheduling. Future work on this project will aim to improve these models, and test their robustness over longer periods of monitoring.

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