INTRODUCING AN INTEGRATED FRAMEWORK TO OPTIMZE COTTON VARIABLE RATE IRRIGATION IN HUMID REGIONS

A. Haghverdi and B.G. Leib

Biosystems Engineering & Soil Science Department
University of Tennessee
Knoxville, Tennessee

ABSTRACT

The need to avoid yield loss from drought stress along with increased commodity prices have caused a significant conversion of rainfed to irrigated production in humid regions. Management of cotton supplemental irrigation in humid regions is challenging due to significant spatial variation of the soil physical characteristics as well as temporal changes in rainfall patterns. This study aimed to introduce a practical framework to optimize cotton supplemental variable rate irrigation in humid regions.

Keywords: pedotransfer function, variable rate irrigation, production function

INTRODUCTION

Cotton supplemental irrigation management in humid regions

The growing demand for food and fiber production along with the intrinsic uncertainty in rainfall patterns, due to climate variability, has focused great attention on irrigation. World agricultural production has grown between two and four percent per year on average over the last fifty years while irrigation has doubled in the same time period (FAO, 2013). Irrigation accounts for only 17% of the land area utilized for agriculture (Fereres and Connor, 2004), yet more than 40% of the total food production comes from irrigated areas (FAO, 2013).

At the same time, precision agriculture (PA) is moving forward in line with the significant achievements in instrumentation, measurements and data-processing. This revolution is changing the concept of an agricultural unit from farm to sub-field by providing precision management opportunities for farmers. The National Research Council definition of PA comprises three components: gathering data, analyzing data and subsequently managing the farm, based on the result at an appropriate scale and time (Oliver 2010).

With precision agriculture technology, farmers have the means to collect the information needed to optimize site-specific variable-rate irrigation. In fact, they have the facilities to conduct customized research that has been traditionally reserved for research farms with small plots. The parameters that are needed for site specific irrigation are related to components in the soil-water-crop-atmosphere continuum. Most farmers in one way or another in west TN have access to precision farming equipment. Precision farming provides a unique opportunity to continuously produce valuable sources of information. An enormous amount of data is now obtained having extremely valuable information about temporal and spatial changes in each field. Yield maps are the most readily available information, while other data such as soil apparent electrical conductivity (ECa) maps and elevation maps are also to a great extent available. If not, they could be collected without spending a considerable amount of time and money.

Cotton is one of the major crops in west TN which is also vital for the US economy since it is an essential export-oriented product (Adams et al., 2006). Cotton supplemental irrigation is growing fast in west TN. The temporal pattern of rainfall changes from year to year with unexpected drought periods likely to occur each growing season. Consequently, producers are more willing to invest in irrigation systems to prevent any yield loss. That is why studying cotton lint yield-irrigation relationship is extremely important. Gwathmey et al. (2011) investigated the cotton responses to supplemental irrigation in Jackson TN in a 4-year study. They observed irrigation treatment significantly improved lint yield (i.e. 38 % in average at the 2.54 cm wk^{-1} irrigation rate) in comparison with the rainfed treatment in 3 of 4 years.

Optimizing cotton supplemental variable rate irrigation (VRI) management is challenging. Conventional irrigation management tries to answer when and how much to irrigate but VRI management ought to address where to irrigate as well. Within field soil variation is common in west TN with respect to soil hydraulic and physical properties. Given soil spatial variation under single irrigation systems in this region, Duncan (2012) concluded VRI is the desired irrigation scenario to optimize cotton lint yield. He illustrated that a single irrigation decision cannot optimize the cotton lint yield for soils with significantly different water holding capacity in west TN. Precision irrigation center pivots have been commercially available for a while. In addition, most of the available center pivots in west TN are able to vary the irrigation across fields to some extent by changing their travel speed in pie shaped zones. This study aimed to categorize the challenges in optimizing cotton supplemental VRI and to establish a practical framework to address those challenges.

PROPOSED FRAMEWORK

Figure 1 illustrates the proposed framework to schedule the cotton variable rate irrigation in humid regions. The framework consists of four phases to address four different challenges. The prime modeling method in this framework is neural networks due to its promising performance predicting soil hydraulic information and crop yield (Haghverdi et al., 2012; Haghverdi et al., 2014a; Haghverdi et al., 2014b). However, the framework was designed such that it works for other crops using other modeling techniques as well.

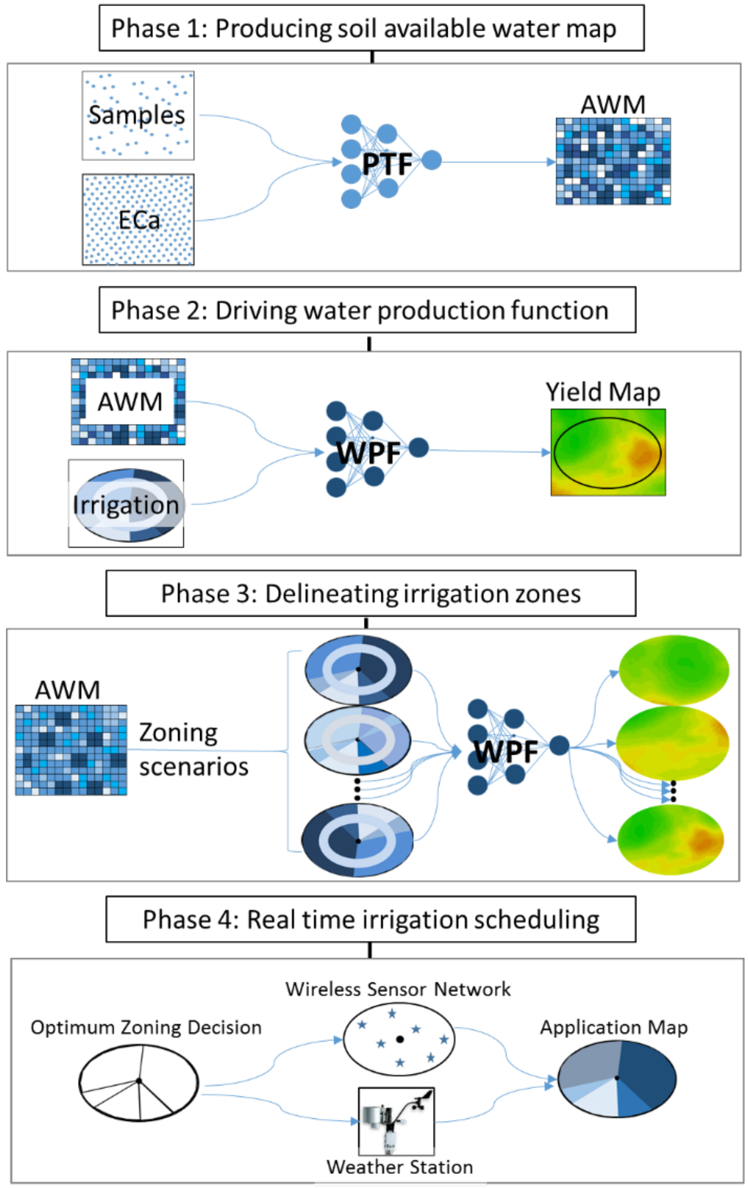

Fig. 1. A sketch of the proposed method to optimize cotton variable rate irrigation in humid regions. PTF: Pedotransfer function; WPF: water production function; AWM: available water map; ECa: apparent electrical conductivity.

Challenge 1: field-scale spatial variation of soil

Soil hydraulic information is required for irrigation scheduling but is categorized as hard-to-obtain data. Collecting soil hydraulic information is challenging due to the time and labor consuming nature of the laboratory and in situ methods. When it comes to variable rate irrigation, there is the extra difficulty of providing a high resolution soil hydraulic map from a limited number of discrete measured locations.

The most widely accepted method to fulfill the need for soil water retention information is called a pedotransfer function (PTF). The well-known PTFs (e.g.

Rosetta by Schaap et al. (2001) and kNearest by Nemes et al. (2008)) are useful tools to convert basic soil information to soil hydraulic data with a reasonable degree of accuracy, yet there are two major concerns hampering their application for providing enough data for variable rate irrigation: (i) They are not spatial tools and therefore cannot generate a map and (ii) the input predictors of them are hard to obtain in practice for high resolution mapping. Grid sampling and subsequently using geostatistical methods is the most accepted way to map soil properties. However, a relatively large number of samples are needed to establish accurate high-resolution soil maps (Zhao et al., 2009) which is costly and time consuming (Saey et al., 2009).

The evidence in the literature (e.g. Abdu et al. (2008); Duncan (2012); Saey et al. (2009)) seems to point toward dense data sets, such as apparent electrical conductivity (ECa) with calibration and verification from limited soil core data, as a promising solution to overcome abovementioned problems. EC is an indicator showing salinity in arid regions. In humid regions, where salinity is not a major factor, EC may provide some useful information about clay percentage, cation exchange capacity (CEC) and water content (Sudduth et al. 2005). Duncan (2012) showed depth to sand layer and available water holding capacity of soil was strongly related to ECa data in an irrigated cotton field at west TN research station. Sudduth et al. (2005) tried to relate ECa to soil properties across the north-central USA. They showed a relatively high correlation between ECa with clay and CEC across all study fields but this correlation was only available in a limited number of fields between soil moisture and ECa. McCutcheon et al. (2006) reported a weak temporal uniformity in ECa data when mapped in a dryland field over time. They found volumetric soil water content was the dominant factor which affects the ECa variability in both spatial and temporal manners.

In the first phase of the proposed framework, a high resolution crop available water map is generated using soil core information, ECa data and a PTF. The PTF converts measured soil basic data to crop available water. Afterwards ECa data is used to generate a high resolution map using an appropriate interpolation technique.

Challenge 2: dynamic yield-soil-water relationships

To identify an optimum irrigation scenario, the mathematical relationship between applied irrigation and cotton lint yield should be known. Duncan (2012) showed that this relationship is substantially different among soils with different water holding capacities. In conventional agriculture, one predicts average yield across the field and ignores yield variation within the field. In precision agriculture, however, the goal is to consider and to manage within-field yield variation. As a result, understanding and modeling the effect of applied irrigation water on crop yield in a spatio-temporal scheme becomes a crucial challenge in optimizing VRI.

Crop growth models and empirical equations are useful tools to quantify the irrigation effect on crop yield. The crop models were shown to be precise, yet they need lots of input data. Classical water production functions (WPFs) need less data, but there are some shortcomings associated with them. WPFs, like other regression-based equations, are relatively easy to build but are mostly linear and not powerful enough to model complex ecological systems (Dai et al., 2011). They are derived based on limited observations thus are only valid for a single crop at a specific location. That is why their performances should be tested carefully in advance to use them for irrigation planning and establishment of water management plans (Igbadun et al., 2007). In practice, poorly calibrated crop growth models are not a better option than empirical tools. In summary, the balance between simplicity and accuracy of the models should be considered as a critical issue when applying them in broad practices (Farahani et al., 2009).

Spatial yield prediction at a high spatial resolution is required in precision agriculture studies. Crop growth models are robust enough to deal with temporal changes but they are point-based and not able to cover spatial variation in their calculation. Dividing the field into homogenous sub-units, using interpolation techniques and model parameterization at a high spatial resolution are possible methods to solve this issue (Florin, 2008). However, all of these methods are time-consuming and costly and not practical in majority of situations. Promising results have been reported recently for the application of data mining methods to predict crop yield in conventional and precision agriculture practices (e.g. Haghverdi et al., 2014a; Ruß and Brenning, 2010).

In the second phase, an in situ irrigation study is implemented applying different irrigation amounts across field. The irrigation experiment should be designed to provide maximum information on soil-water-yield relationships. Site specific spatial WPFs using data mining algorithms, then, are derived each year to investigate the effect of different irrigation scenarios on cotton yield variation.

Challenge 3: delineation of irrigation management zones

One of the steps in precision agriculture is to delineate management areas within fields where it is expected that applying identical treatment will cause significant yield differences. A corollary expectation is that varying the treatment of these areas will facilitate optimizing yield. In practice, number of zones is dependent on the target input and available equipment.

Map-based and sensor-based approaches are two major methods to practice variable-rate application. In the map-based method, application maps are prepared using site-specific information such as yield data and soil data prior to implementation. In the sensor-based method, a real time decision on application rate is made using data collected via sensors and pre-developed application algorithms (Thöle et al., 2013). Variable rate irrigation can be a combination of both methods i.e. a map showing irrigation management zones where sensors identify real time application rates for each zone.

There are only a few studies on deriving management zones for variable rate irrigation. Jiang et al. (2011) used the physical properties of soil as the data source to delineate irrigation zones. They utilized management zone analysis software which uses a fuzziness performance index and normalized classification entropy for identifying the least number of subzones. Bereuter (2011) studied zoning techniques on irrigated corn in Nebraska. Nine soil and landscape attributes were chosen as potential factors for zoning. Results showed that different combinations of selected attributes were suitable for zoning at different sites.

There are several methods to delineate management zones. Applying unsupervised clustering techniques and user-defined zoning are the main procedures. Clustering techniques group similar data points (cells) into distinct classes. Methods such as k-means and fuzzy k-means has been widely used to identify management zones (Córdoba et al., 2013). However, there are some limitations associated with zoning for variable rate irrigation that are not considered in other variable rate applications and have been mostly ignored in current studies. First, the number and size of irrigation zones is limited by properties of the irrigation system. Second, a dynamic temporal zoning system may be required considering soil-crop-water relationships. Even available precision irrigation systems are not able to apply water with the same resolution as one can apply other variable rate applications such as fertilizer. Most irrigation systems in humid regions are only able to vary the irrigation across fields within limited pie-shaped zones. In this case, the optimum location of pies as well as optimum application rates for each pie should be identified.

In the third phase, irrigation zones will be delineated. The crop available water map is utilized to delineate the initial zones. Afterwards the best zoning scheme is selected as the one that is predicted to produce the highest yield using the WPFs. The second and third phases need to be repeated for each cropping season in order to find the optimum temporal stable zones.

Challenge 4: real time irrigation scheduling under temporal variability

The last challenge is the season-to-season variability in rainfall patterns. Surprisingly, irrigation management for optimizing cotton yield in a humid region is more complicated than that in an arid region because unpredictable rainfall patterns prevent a static irrigation schedule that works all the time. Excess water content in root zone could occur due to overlapping irrigation events with rainfall. This may cause yield reduction either because of lack of aeration or by causing a crop to unnecessarily increase biomass but not yield. Bajwa, and Vories (2007) demonstrated that excessive irrigation in wet weather conditions decreased cotton lint yield in Arkansas. On the other hand, severe in-season drought conditions for a short period of time are likely to occur in a humid region when lack of irrigation would significantly reduce yield.

Soil moisture is the most widely used indicator for irrigation scheduling (Leib et al., 2012; Leib et al., 2003). Recent advances in wireless communication makes it more feasible to monitor soil water status in multiple locations within a field which is required for scheduling variable rate irrigation systems. Pan et al. (2013) established a framework to manage irrigation in a field with soil spatial variation by means of information available in precision agriculture (i.e. field elevation and apparent electrical conductivity), wireless sensing technology and site specific derived equations. In another study, Hedley and Yule (2009a) produced soil hydraulic maps using regression equations from high resolution EC maps. They added a daily time step to the generated map to be able to spatially estimate soil water status across the field by means of a network of wireless soil moisture sensors. Hedley and Yule (2009b) found that daily soil water content mapping could be utilized to manage a variable rate irrigation system.

In the last phase, a wireless network of sensors is implemented to monitor soil water status within each zone while site-specific weather data will be collected to calculate ET. Water balance and/or ET data is used for real time irrigation scheduling.

REFERENCES

Abdu, H., Robinson, D. A., Seyfried, M., and Jones, S. B. 2008. Geophysical imaging of watershed subsurface patterns and prediction of soil texture and water holding capacity. Water Resour. Res., 44(4).

Adams, G., Slinsky, S., Boyd, S., Huffman, M. 2006. The Economic Outlook for U.S. Cotton 2006. National Cotton Council of America, pp. 1–78, http://www.cotton.org/econ/ reports/upload/2006-Annual-Economic-Outlook.pdf (last verified on March 4, 2007).

Bajwa, S. G., and Vories, E. D. 2007. Spatial analysis of cotton (Gossypium hirsutum L.) canopy responses to irrigation in a moderately humid area. Irrig. Sci. 25(4), 429-441.

Bereuter, A. M. 2011. Management Zone Delineation Techniques on Irrigated Corn in Nebraska. Thesis, University of Nebraska - Lincoln. http://digitalcommons.unl.edu/agronhortdiss/40

Córdoba, M., Bruno, C., Costa, J., & Balzarini, M. 2013. Subfield management class delineation using cluster analysis from spatial principal components of soil variables. Comput. Electron. Agric. 97, 6-14.

Dai, X., Huo, Z., and Wang, H. 2011. Simulation for response of crop yield to soil moisture and salinity with artificial neural network. Field Crops Res. 121(3), 441-449.

Duncan, H. A. 2012. Locating the Variability of Soil Water Holding Capacity and Understanding Its Effects on Deficit Irrigation and Cotton Lint Yield.

FAO. Agriculture Organization of the United Nations, 2012. FAO statistical yearbook.

Farahani, H.J., Izzi, G., and Oweis, T.Y. 2009. Parameterization and evaluation of the AquaCrop model for full and deficit irrigated cotton. Agron. J. 101(3), 469-476.

Fereres, E., and Connor, DJ. 2004. Sustainable water management in agriculture. In: Cabrera E, Cobacho R, eds. Challenges of the new water policies for the XXI century. Lisse, The Netherlands: A.A. Balkema, 157–170.

Florin, M. 2008. Towards precision agriculture for whole farms using a combination of simulation modelling and spatially dense soil and crop information. Ph.D. thesis. http://hdl.handle.net/2123/3169.

Gwathmey, C.O., Leib, B.G., and Main, C.L. 2011. Lint yield and crop maturity responses to irrigation in a short-season environment. J. Cotton Sci. 15(1), 1-10.

Haghverdi, A., Cornelis, W.M., and Ghahraman, B. 2012. A pseudo-continuous neural network approach for developing water retention pedotransfer functions with limited data. J. Hydrol. 442, 46-54.

Haghverdi, A., Ghahraman, B., Leib, B. G., Pulido-Calvo, I., Kafi, M., Davary, K., & Ashorun, B. 2014a. Deriving data mining and regression based water-salinity production functions for spring wheat (Triticum aestivum). Comput. Electron. Agric. 101, 68-75.

Haghverdi, A., Öztürk, H. S., and Cornelis, W. M. 2014b. Revisiting the pseudo continuous pedotransfer function concept: Impact of data quality and data mining method. Geoderma, 226, 31-38.

Hedley, C. B., and Yule, I.J. 2009a. A method for spatial prediction of daily soil water status for precise irrigation scheduling. Agric. Water Manage. 96(12), 1737-1745.

Hedley, C.B., and Yule, I.J. 2009b. Soil water status mapping and two variable-rate irrigation scenarios. Precision Agric. 10(4), 342-355.

Igbadun, H.E., Tarimo, A.K.P.R., Salim, B.A., and Mahoo, H.F. 2007. Evaluation of selected crop water production functions for an irrigated maize crop. Agr. Water Manage. 94(1-3), 1-10.

Jiang, Q., Fu, Q., and Wang, Z. 2011. Delineating site-specific irrigation management zones. Irrig. Drain. 60(4), 464-472.

Leib, B. G., J. D. Jabro, and G. R. Matthews. 2003. Field evaluation and performance comparison of soil moisture sensors. Soil Sci. 168(6):396-408.

Leib, B. G., C. Perry, and K. Fisher. 2012. Section 6: Sensor based scheduling. Cotton Irrigation Management for Humid Regions. Cotton Incorporated, Cary, NC, Pp 21 to 31.

McCutcheon, M., Farahani, H., Stednick, J., Buchleiter, G. and Green, T. 2006. Effect of soil water on apparent soil electrical conductivity and texture relationships in a dryland field. Biosystems Eng. 94(1), 19-32.

Nemes, A., Roberts, R.T., Rawls, W.J., Pachepsky, Y.A., and van Genuchten, M.T. 2008. Software to estimate− 33 and− 1500kPa soil water retention using the non-parametric k-Nearest Neighbor technique. Environ. Model Soft. 23(2), 254-255.

Oliver, M. 2010. Geostatistical Applications for Precision Agriculture, pp. 1-34, Springer.

Pan, L., Adamchuk, V.I., Martin, D.L., Schroeder, M.A., and Ferguson, R.B. 2013. Analysis of soil water availability by integrating spatial and temporal sensor-based data. Precision Agric. 1-20.

Ruß, G., & Brenning, A. 2010. Data mining in precision agriculture: management of spatial information. In Computational Intelligence for Knowledge-Based Systems Design (pp. 350-359). Springer Berlin Heidelberg.

Saey, T., Van Meirvenne, M., Vermeersch, H., Ameloot, N., and Cockx, L. 2009. A pedotransfer function to evaluate the soil profile textural heterogeneity using proximally sensed apparent electrical conductivity. Geoderma, 150(3), 389-395.

Schaap, M.G., Leij, F.J., and van Genuchten, M.T. 2001. ROSETTA: a computer program for estimating soil hydraulic parameters with hierarchical pedotransfer functions. J. hydrol. 251(3), 163-176.

Sudduth, K.A., Kitchen, N.R., Wiebold, W.J., Batchelor, W.D., Bollero, G.A., Bullock, D.G., Clay, D.E., Palm, H.L., Pierce, F.J., Schuler, R.T. and Thelen, K.D. 2005. Relating apparent electrical conductivity to soil properties across the north-central USA. Comput. Electron. Agric. 46(1–3), 263-283.

Thöle, H., Richter, C. and Ehlert, D. 2013. Strategy of statistical model selection for precision farming on-farm experiments. Precision Agric. 1-16.

Zhao, Z., Chow, T.L., Rees, H.W., Yang, Q., Xing, Z. and Meng, F.-R. 2009. Predict soil texture distributions using an artificial neural network model. Comput. Electron. Agric. 65(1), 36-48.