In typical applications of the volume balance method, infiltration is assumed to depend on opportunity time only and various procedures are available to calculate V_z^* under those conditions (Strelkoff et al, 2009). In this analysis, Eqs.(4) and (2) depend on the flow depth variation along the field and with time, $y(x,t)$, and on the unknown parameters K_s and c.

Estimates of Manning n were developed by fitting the simulated flow depths as a function of distance and time to the measured values. Since estimates of V_y with Eq.(7) depend on the roughness parameter, the overall analysis required first estimating first the infiltration function based on an assumed n value. Unsteady simulation was then conducted with that function and the resulting depths were used to adjust n. Volume balance analysis results were then updated with the new n. No further adjustments to n were required after this step, even with further changes to the infiltration parameters.

Modifications of the parameter estimation procedures for flow-depth dependent infiltration

EVALUE uses a two-step process for the estimation of flow-depth dependent infiltration parameters (Bautista and Schlegel, 2017). The first step consists of the estimation of an empirical infiltration function, dependent on opportunity time only and, thus, independent of wetted perimeter variations along the furrow and with time. The Modified Kostiakov equation is used in this initial stage:

$$A_z = W_1\left(k\tau^a + b\tau\right) + W_2 c \tag{9}$$

In Eq.(9), k, a, b, and c are empirical parameters with appropriate units and W_1 and W_2 are transverse widths [L]. For this analysis, both W_1 and W_2 were set equal to the furrow spacing FS. Equation (8) is expressed as a function of the parameters of Eq. (9) and used to solve Eq.(5) based on the available volume balance data.

In the second step, an unsteady flow simulation is conducted with the estimated empirical infiltration function. This simulation produces the $y(x,t)$ needed to solve Eq. (8), and subsequently, (5). This step relies on the non-uniqueness of solutions to the infiltration parameter estimation problem: nearly identical flow depth and flow rate conditions can be simulated with different infiltration functions as long as those functions predict the same average infiltration (Bautista 2016).

Determination of θ_0, θ_s and h_f

As was previously indicated, the Elliott report includes gravimetric water content and bulk density data. Those data, measured only for one furrow within a group, at a limited number of stations, and at 30 cm depth intervals, revealed variations in the initial volumetric water content with depth and distance. For simplicity, and since the analysis assumes a uniform soil profile, those data were averaged to determine θ_0 for each group and irrigation event (Table 2). Since no measurements were obtained for Irrigation 3, Group 2, the initial water content was assumed equal to 0.32, based on the values given in the table for other irrigations in the same group.

Table 2. Initial volumetric water content for each furrow group and irrigation

Irrigation	Group 1	Group 2
1	0.30	0.33
2	0.28	0.32
3	0.27	
4	0.28	0.32
5	0.26	0.29

Rawls et al. (1983) reported values for parameters of the Green-Ampt equation based on soil texture. The average values reported for a clay loam soil, θ_s = 0.45 and h_f = 43 cm, were selected for this study. Subsequent sensitivity analyses showed that the estimation is far more sensitive to K_s and c than to θ_s and h_f.

RESULTS

Figure 1 displays the estimated infiltration parameters K_s and c. Note first that the estimated hydraulic conductivities, which range from 0.28-0.98 cm/h, were consistent with values reported in the literature for a clay loam soil (Rawls et al., 1983; Saxton and Rawls, 2006). The values in this figure were averaged by irrigation and group and results are presented in Table 3. Average hydraulic conductivity differs between groups, and tends to decline during the irrigation season, more strongly for furrows in Group 1 than in Group 2. Hydraulic conductivity differences between furrows were relatively consistent throughout the season (Figure 1) and can probably be attributed to differential compaction.

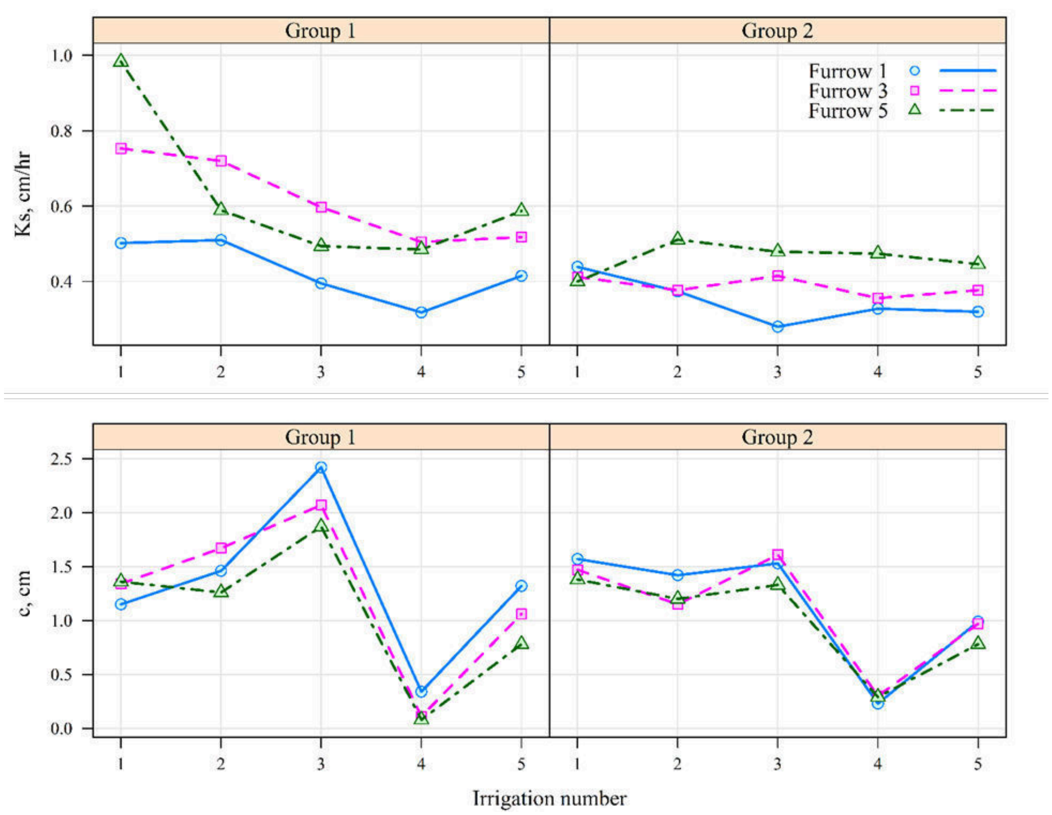

Figure 1. Estimated hydraulic conductivity and macroporosity for each furrow, group, and irrigation event.

Table 3. Average WGA model parameters for each group and irrigation event

	K_s		c	
Irrigation	Group 1	Group 2	Group 1	Group 2
1	0.75	0.42	1.28	1.47
2	0.61	0.42	1.46	1.26
3	0.50	0.39	2.12	1.49
4	0.44	0.39	0.18	0.27
5	0.51	0.38	1.05	0.91
Average	0.56	0.40	1.22	1.08

Estimates of the macropore parameter c varied mostly between irrigations, although some differences can be noted between groups for Irrigation 3 (Figure 1 and Table 3). Differences between furrows within a group and irrigation event were much smaller (Figure 1). With both groups, the c estimates were smallest, on average, for Irrigation 4. In contrast, the average macropore value was largest for Group 1, Irrigation 3. Although water content is believed to be a factor that influences the development of cracks and macropores, no relationship is evident between the estimated values of c and the initial water contents of Table 3. It should be noted, however, that the shortest interval between irrigations (8 days versus 12 days for other events) corresponds to Irrigation 4, and this may explain why the macropore term c is much smaller for this event.

From the results of Figure 1, correlation between the estimated parameters is difficult to assess. For example, with Group 1, K_s decreases for all furrows between Irrigations 2 and 4 while the parameter c increases and then decreases. Likewise, with Group 2, each parameter seems to exhibit a different pattern of variation, which depends mostly on the irrigation event. At the same time, note that Furrow 1, Group 1 produced for all irrigation events the smallest values of K_s and, mostly, the largest values for c (except for Irrigations 1 and 2). A similar pattern is suggested by the results of Group 2. Hence, it is possible infiltration through the soil matrix may be slightly underestimated with the proposed estimation approach when infiltration through the macropores is large.

It is important to recall that these parameter were estimated using pedotransfer function-derived values for θ_s and h_f, and that the parameter γ is embedded with the estimated K_s. The potential range of variation for h_f can be expected to be greater than for θ_s and impact the K_s and c estimates. Initial sensitivity analysis have suggested a limited effect, but additional testing is needed.

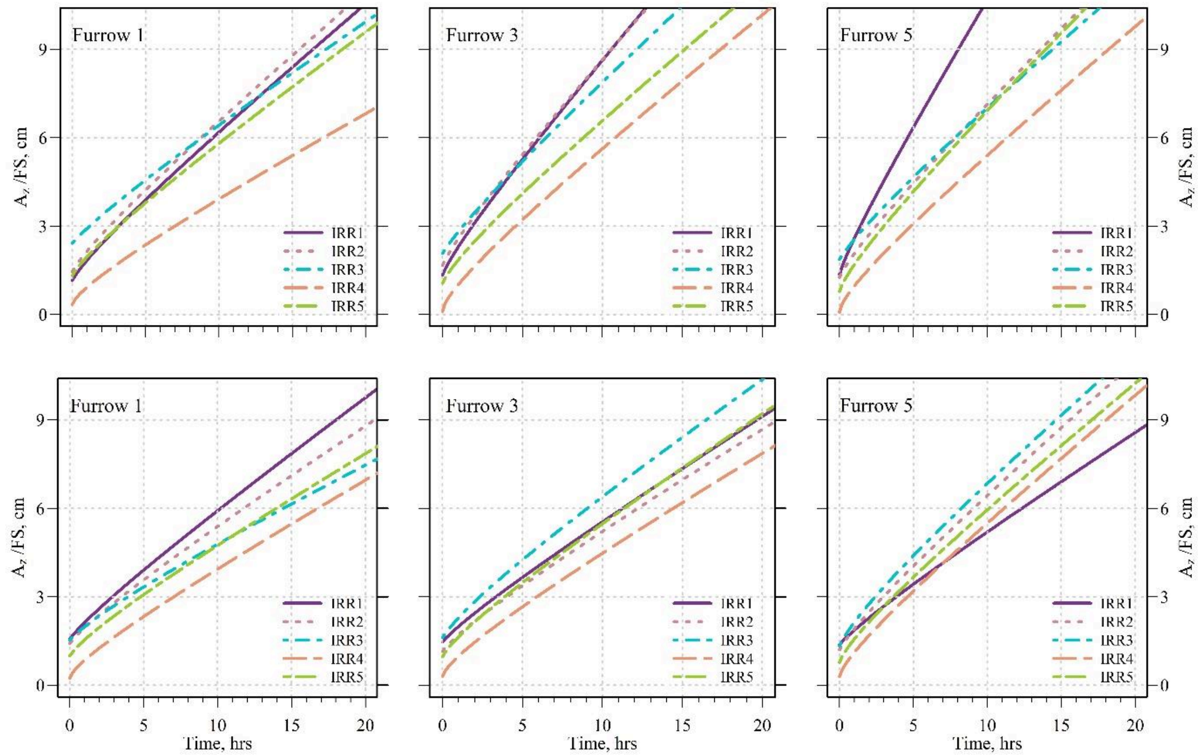

Figure 2. Infiltration functions for each furrow and irrigation event.

Plots of the infiltration functions (Figure 2) help further understand the spatial and seasonal variations in intake characteristics for these furrows. These curves were computed for a common flow rate, roughness coefficient, and furrow cross-section to eliminate the effect of variable flow conditions among the tests. Like the estimated parameter values, these results suggest that furrows in Group 1 have larger infiltration rates than those in Group 2, and also that infiltration rates tend to decline as the irrigation season progresses. Two exceptions need to be noted, however. First, the functions developed for Irrigation 1 mostly predict larger infiltration rates than for other events, but with Furrow5, Group 2 it predicts the lowest infiltration rates, and with Furrow 3, Group 2 the curve plotted in the middle of all events. Infiltration characteristics tend to be most variable early during the irrigation season due to differences in soil consolidation, and this may be a factor that accounts for these results. Measurement errors could also explain these results. The second exception are the results of Irrigation 4, which display consistently lower infiltration rates than those computed for Irrigation 5. Again, the short interval between Irrigations 3 and 4 may explain why the lowest infiltration rates are associated, mostly, with Irrigation 4.

When conducting a hydraulic analysis of an irrigation system, a key consideration is the time needed to infiltrate a typical irrigation target. The infiltrated depth for the Benson irrigations was generally around 6 cm. The plots of Figure 2 provide a measure of how infiltration variability complicates the design and management of furrow irrigation systems. For a 6 cm target, the required opportunity time varies between about 5 and 17 hours. Evidently, some of this variation is an artifact of our evaluation procedures. However, much of this variation is also the result of small differences in the values of K_s, which as was noted earlier, seem to vary consistently for most furrows from one irrigation event to the next.

Figure 3 illustrates the relationship between the estimated macropore parameter *c* and the infiltrated volume during advance V_{z_adv}. If c is a realistic measure of the macropore volume in a furrow, then these results show that V_{z_adv} is strongly correlated with *c*. A noticeable outlier is a value computed for Irrigation 1, Furrow 5 which, as was discussed earlier, are results that could be affected by soil structural conditions and/or measurement errors.

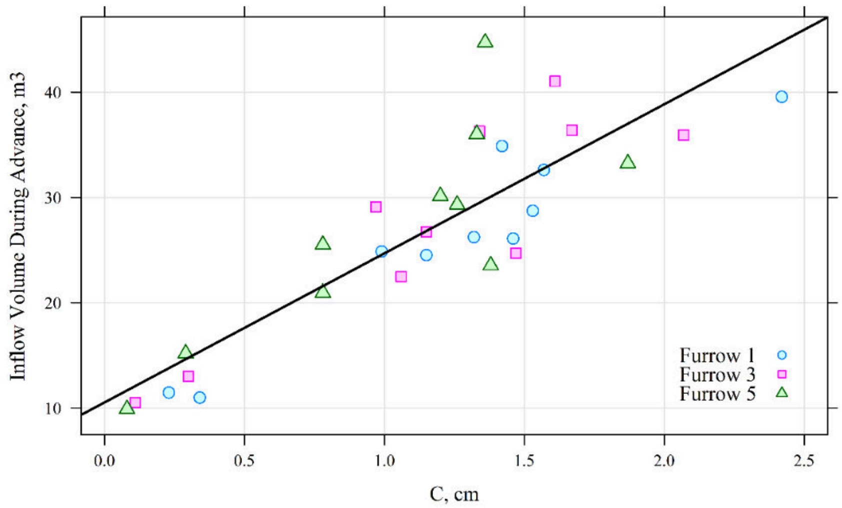

Figure 3. Variation of infiltrated volume during advance with the estimated macroporosity parameter *c*

The estimated values for the Manning *n* (Figure 4) suggest that hydraulic resistance increased slightly as the irrigation season progressed. It is unclear why *n* varied over a wider range for furrows in Group 2 than for Group 1. Except for Group 1, Irrigation 3, similar Manning *n* estimates were computed for all furrows in a Group and Irrigation event. A Manning *n* value of 0.04 is typically recommended for bare furrows, but these results clearly show that much lower values can be encountered in practice.

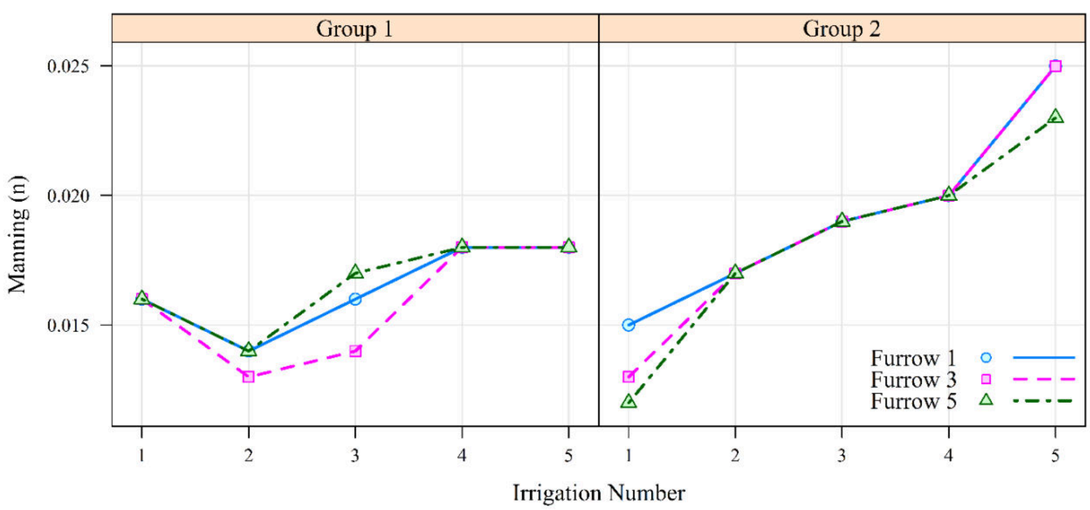

Figure 4. Variation in the estimated Manning n as a function of furrow, group, and irrigation event.

The estimated infiltration and roughness parameters were used to simulate the corresponding irrigation event. With all data sets, simulation results were reasonably accurate in comparison with the available measurements (advance and recession times, outflow rates, and flow depths). For many of the events, better simulation results were generated when predicting infiltration WGA model than with Eq.(9). An indicator of the goodness-of-fit is the difference between average opportunity time computed from the field data and from simulation. This difference was no greater than 3 min for all tests.

CONCLUSIONS

Three main conclusions emerge from this analysis. First, the proposed WGA equation in combination with macropore infiltration component, appears to model furrow infiltration reasonably at least for the range of soil and hydraulic conditions examined here. While the concept of a volume water that infiltrates instantaneously seems unrealistic, such an approach appears to be a practical way for representing the infiltration flow at short times. One potential way for improving the model is to limit infiltration to the flow rate provided by the irrigation stream.

The estimation procedure presented herein produced consistent results for the infiltration and roughness parameters. The estimated K_s were of similar magnitude as values reported in the literature. Moreover, differences between values computed for different furrows tended to vary systematically during the season, and those values mostly displayed gradual changes for each furrow during the irrigation season. The macroporosity parameter c exhibited greater variation than K_s, but mostly between irrigation events and less between furrows for an irrigation event.

Last, results suggest that the variability of infiltration, measured in terms of the opportunity time needed to infiltrate a typical irrigation target, can be substantial and largely a function of slight differences in hydraulic conductivity between furrows.

This analysis assumes that the macropore term is a function of furrow spacing, and thus that water does not flow between neighboring furrows. The fact that c is relatively consistent for an irrigation event suggests that this assumption is largely true. On the other hand, the analysis also assumes that water that infiltrates through macropores does not flow past the root zone. Accounting for bypass flow is necessary to better understand the ultimate distribution uniformity of irrigation.

REFERENCES

Bautista, E. (2016). "Effect of Infiltration Modeling Approach on Operational Solutions for Furrow Irrigation." *J. Irrig. Drain. Eng.*, 142(12), 06016012.

Bautista, E. and Schlegel, J.L. (2017). “A flexible system for the estimation of infiltration and hydraulic resistance parameters in surface irrigation.” *Trans. ASABE*. Submitted for publication.

Bautista, E., Strelkoff, T., Clemmens, A.J. (2012). "Improved surface volume estimates for surface irrigation balance calculations." *J. Irrig. Drain. Eng.*, 138, 715-726.

Bautista, E. and Wallender, W. W. (1985). "Spatial variability of infiltration in furrows." *Trans. ASAE*, 28(6), 1846-1851, 1855.

Bautista, E., Warrick, A. W., and Strelkoff, T. S. (2014). "New results for an approximate method for calculating two-dimensional furrow infiltration." *J. Irrig. Drain. Eng.*, 140(10), 04014032.

Bautista, E., Warrick, A. W., Schlegel, J. L., Thorp, K. R., and Hunsaker, D. J. (2016). "Approximate furrow infiltration model for time-variable ponding depth." *J. Irrig. Drain. Eng.*, 0(0), 04016045.

Beven, K.J. and Clarke R.T. (1986). "On the variation of infiltration into a homogeneous soil matrix containing a population of macropores." *Water Res. Res*. 22(3): 383–388

Childs, J. L., Wallender, W. W., and Hopmans, J. W. (1993). Spatial and seasonal variation of furrow infiltration. *J. Irrig. Drain. Eng.*, 119(1), 74-90.

Clemmens, A. J., and Bautista, E. (2009). "Toward physically based estimation of surface irrigation infiltration." *J. Irrig. Drain. Eng.*, 135(5), 588-596.

Enciso-Medina, J., Martin, D., and Eisenhauer, D. (1998). "Infiltration model for furrow irrigation." *J. Irrig. Drain. Eng.*, 124(2), 73-79.

Gillies, M. H., Smith, R. J., and Raine, S. R. (2011). "Evaluating whole field irrigation performance using statistical inference of inter-furrow infiltration variation." *Biosystems Eng*., 110(2), 134-143.

Green, W. H., and Ampt, G. A. (1911). "Studies on soil physics. 1: The flow of air and water through soils." *J. Agric. Sci*., 4(1), 1–24.

Izadi, B., and Wallender, W. W. (1985). "Furrow hydraulic characteristics and infiltration." *Trans. ASAE*, 28(6), 1901-1908.

Jaynes, D. B. (1990). "Temperature variations effect on field-measured infiltration." *Soil Sci. Soc. Am. J.*, 54(2), 305-312.

Jaynes, D. B., and Hunsaker, D. J. (1989). "Spatial and temporal variability of water content and infiltration on a flood irrigated field." *Trans. ASAE*, 32(4), 1229-1238.

Oyonarte, N. A., Mateos, L., and Palomo, M. J. (2002). "Infiltration variability in furrow irrigation." *J. Irrig. Drain. Eng.*, 128(1), 26-33.

Rawls, W. J., Brakensiek, D. L., and Miller, N. (1983). "Green-Ampt infiltration parameters from soils data." *J. Hyd. Eng*., 109(1), 62-70.

Saxton, K.E. and Rawls, W.J. (2006). "Soil water characteristic estimates by texture and organic matter for hydrologic solutions." *Soil Sci. Soc. Am. J*., 70(5): 1569-1578

Strelkoff, T. S., Clemmens, A. J., and Bautista, E. (2009). "Estimation of soil and crop hydraulic properties." *J. Irrig. Drain. Eng.*, 135(5), 537-555.

Trout, T. J. (1990a). "Furrow inflow and infiltration variability impacts on irrigation management." *Trans. ASAE*, 33(4), 1171-1178.

Trout, T. J. (1990b). "Surface seal influence on surge flow furrow infiltration." *Trans. ASAE*, 33(5), 1583-1589.

Trout, T. J. (1992). "Furrow flow velocity effect on hydraulic roughness." *J. Irrig. Drain. Eng.*, 118(6), 981-987.

Trout, T. J., and Johnson, G. S. (1989). "Earthworms and furrow irrigation infiltration." *Trans. ASAE*, 32(5), 1594-1598.

Walker, W. R., and Kasilingam, B. (2004). "Another look at wetted perimeter along irrigated furrows - Modeling implications." *Critical Transitions in Water and Environmental Resources Management.* Proc. 2004 World Water & Env. Res. Cong. EWRI/ASCE. Salt Lake City, UT; 27 June - 1 July 2004, pp. 1664-1670.

Warrick, A. W. (2003). *Soil Water Dynamics*, Oxford University Press, New York.

Warrick, A. W., Lazarovitch, N., Furman, A., and Zerihun, D. (2007). "Explicit infiltration function for furrows." *J. Irrig. Drain. Eng.*, 133(4), 307-313.

Development of a Smart Water Distribution System (WDS) for Irrigation

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Abstract

With the advancement of computation and sensor technology, new strategies and tactics are being employed in the development of state-of-art operations tools in energy and water resources management. As agriculture is one of the sectors that consumes significant amount of energy and water, these cutting edge tools are particularly important for their management. While one strategy to save energy cost may come from the optimum pump operation considering peak and off-peak hours, the real energy reduction can result from monitoring the water conveyance system regularly and delivering the true water demand at optimum pressure requirement. Similarly, water consumption can be reduced by calculating the true water demand, using correct irrigation method, application time and frequency, and monitoring the conveyance system. This study proposes a framework to reduce energy and water usage in irrigation water distribution system (WDS) by quantifying correct crop water demands through utilization of soil moisture information, weather data, and hydraulics information including flow and pressure throughout the system. Results show that about 13 to 24% water savings is possible when feedback from soil moisture sensor is considered. Similarly, additional 10% water savings is possible if field capacity is considered to be the upper limit for irrigation which will save about 6% of pumping energy consumption.

INTRODUCTION

Agriculture is the economic sector which consumes the most available fresh water of the world, i.e. 70 % of the total resources, against 20% consumed by industry and 10% for domestic use (UN Water 2009). Due to increasing demand of food production with limited amount of water available, optimizing the use of available water is gaining more attention in current days. To save water farmers switched to the most efficient irrigation technique like drip irrigation. The change in the irrigation practice in California can be clearly observed as the decrement in surface irrigation by 30% and increment in the drip irrigation by 31% from the year 1972 until 2001

(Orang et al. 2008) and decrement in surface irrigation by 37% and increment in drip irrigation by 38% from the year 1972 to 2010 (Tindula et al. 2013).

Water and energy is interlinked. Efficient irrigation method not only saves water but also energy. Reca et al. (2014) developed a model to optimize pumping scheduling to use cost effective-effective tariff. For efficient operations of WDS at lower energy consumptions and cost-effective tariff sensors can be used to collect data. Wireless Sensors Network (WSN) based dynamic and automatic irrigation system can sense and control the real time irrigation management system (Balaji et al. 2014, Nemali and van Iersel 2006). Significant water and energy savings can be obtained through sensors technology (Davis and Dukes 2014, Nautiyal et al. 2014, Grabow et al. 2012, Kim et al. 2009, and Goodchild et al. 2015, Haley and Dukes 2011). Sensor feedback based smart subsurface drip irrigation can be used in practice due to its high water saving potential and increased yield from the field (Ayars et al. 2015, Miller et al. 2014).

Several irrigation projects around the globe highlight the need of smart water distribution system, in terms of water use efficiency and energy conservations (McCulloch et al. 2008, Khriji et al. 2014). Sensors in the field communicates through network and transmits the data to the server for making control decision. Smart irrigation water distribution system based on the feedback from the soil moisture sensors data from the field saves water and energy without having any impact in the yield. Despite having high initial investment, the system pays itself making it sustainable. Moreover, the sensors can monitor the performance of a water distribution system which reduce the maintenance cost. The objective of this study is to develop a smart irrigation water distribution system through the use of sensors data (weather, soil, and hydraulics) that are collected and transmitted to a cloud based storage. The sensors data forms a basis to make irrigation decision which saves water and energy. The approach has been applied to an agricultural field at California State University, Fresno.

METHODOLOGY

Irrigation Method

The irrigation practices commonly used in the field are categorized into four major types as: (i) Surface, (ii) Subsurface, (iii) Sprinkler, and (iv) Drip/Micro Irrigation. For this study drip irrigation is used. Like other irrigation methods, drip irrigation also uses evapotranspiration data to calculate the irrigation amount. The crop evapotranspiration, ET_c can be calculated from reference evapotranspiration, ET_0 using the following equation (Cuenca, 1989):

$$ET_c = ET_0 * K_0 \quad (1)$$

Where, K_c is the crop coefficient. To consider the ground cover reduction, the Food and Agriculture Organization of the United Nations (FAO) proposed the following equation to calculate ET_c (Allen et al. 1998):

$$ET_c = ET_0 * K_c * K_r \tag{2}$$

where, K_r is the ground cover reduction coefficient. If rain occurs, the field irrigation requirement (FIR) can be adjusted as follows (Asawa, 2006):

$$\text{FIR} = \frac{ET_c - R_{eff}}{E_a} \tag{3}$$

where, R_{eff} is the effective rainfall and E_a is the irrigation efficiency. Water should be applied frequently to fulfill the crop water requirement between field capacity (FC) and permanent wilting point (PWP) of the soil. The frequency of the irrigation is calculated by dividing the amount of soil moisture depletion by the rate of consumptive use (Asawa, 2006) i.e.

$$\text{Irrigation Frequency} = \frac{Allowable\ soil\ moisture\ depletion}{Rate\ of\ consumptive\ use} \tag{4}$$

Data Collection

Irrigation efficiency and water saving can be increased by properly positioning the soil moisture sensors in the field (Soulis et al., 2014, Grabow et al., 2012). SMS measures volumetric water content in the field and transmit it to the server through telemetry system. In a large field with variable soil type and texture, the feedback from a single SMS is not enough to schedule the irrigation effectively rather it requires more sensors to represent each soil type. Two SMS are installed to collect SM data from two types of soil found in the study field.

Weather data including evapotranspiration (ET), temperature, solar radiation, relative humidity, wind speed etc. are collected from the California Irrigation Management Information System (CIMIS) station # 80 located near the field. These data are cross-checked with another weather station data placed in the field. Hourly weather data is used to estimate hourly ET_0 and added up over 24 hours to estimate daily ET_0 (CIMIS, 2017).The reference evapotranspiration (ET_0) is multiplied by crop coefficient (K_c) to estimate the crop evapotranspiration (ET_c).

The locations and spacing of the hydraulic sensors should be such that they represent the entire network and at the same time do not miss the critical regions of the network. To monitor water and energy loss in the conveyance system flowmeters and pressure transducers are placed throughout the system. The smart meter has been placed at the pump station to collect energy data to understand the insights of energy consumption pattern which can form the basis to schedule most cost-effective pumping schedule.