ESTIMATION OF INFILTRATION AND HYDRAULIC RESISTANCE IN FURROW IRRIGATION, WITH INFILTRATION DEPENDENT ON FLOW DEPTH

E. Bautista, J. L. Schlegel

ABSTRACT. *Estimation of infiltration and hydraulic resistance model parameters from furrow irrigation evaluation data was investigated. A semi-physical, flow-depth dependent furrow infiltration model was used for the analysis. Macropore infiltration was modeled empirically as a constant volume of water per unit area that is absorbed instantaneously. The estimated infiltration parameters were the saturated hydraulic conductivity and the macropore constant. Hydraulic resistance was modeled with the Manning equation; thus, the estimated resistance parameter was the Manning coefficient. The estimation procedure uses volume balance calculations and unsteady flow simulation. Estimation of the flow-depth dependent infiltration parameters requires first the estimation of an empirical infiltration function, via volume balance, and of the resistance parameter, via unsteady flow simulation. Simulated flow depth hydrographs as a function of distance are then used as inputs for a second set of volume balance calculations with the semi-physical infiltration model. This procedure takes advantage of the fact that similar surface flow conditions (advance and recession times, flow depths, and runoff rate) can be predicted with different infiltration functions. The procedure was tested with two irrigation data sets, each consisting of three furrows. With both data sets, the semi-physical infiltration model fitted the measured volume balance data as well as empirical infiltration models. For each group of furrows, estimates of the hydraulic conductivity were of comparable magnitude and were consistent with published values for the particular soil texture. Likewise, estimates of the macroporosity parameter were consistent for each group of furrows. Estimates of the Manning coefficient suggest very uniform hydraulic resistance. Finally, results show that the effect of flow-depth dependent infiltration on irrigation distribution uniformity depends on soil and hydraulic conditions. For one of the data sets, distribution uniformity computed with the proposed infiltration model was only slightly different from the uniformity computed assuming that infiltration depends only on opportunity time, because of the large macropore flow contribution and the shallow flow conditions.*

Keywords. *Distribution uniformity, Furrows, Green-Ampt, Hydraulic conductivity, Hydraulic modeling, Hydraulic resistance, Infiltration, Inverse modeling, Irrigation, Parameter estimation.*

Essential inputs to surface irrigation simulation models are the functional relationships for infiltration and hydraulic resistance. For a particular field, those functions are defined by appropriately selected and parameterized infiltration and hydraulic resistance models. Currently, the recommended approach for defining those functions is by measuring the response of an irrigation system to a known inflow rate and expressing that response as a function of the unknown parameters through a mathematical model. In the surface irrigation literature, these techniques are commonly described as inverse solutions or parameter estimation methods.

A variety of parameter estimation methods have been proposed for surface irrigation, which differ depending on the data requirements and computational approach (Strelkoff et al., 2009a). The simplest methods use a single measurement of advance time to a known distance. Others use a combination of measurements taken at different stages of the irrigation event. From a computational standpoint, two basic categories can be identified. Volume balance methods explicitly solve for the cumulative infiltrated volume V_z at a given time using the principle of conservation of mass in combination with geometric descriptions of the surface and subsurface profile, without consideration of the dynamics of the flow. Volume balance can be calculated at one or more times during the event. The unknown parameters are found by matching those infiltration volumes with volumes calculated by integrating the infiltration profile as a function of distance, V_z^* (Bautista and Schlegel, 2017). The infiltration profile is a function of the unknown infiltration function and of the distribution of opportunity times along the field, which is determined from field measurements. These methods were developed for the estimation of infiltration alone, but in some instances they can also be used for the estimation of hydraulic resistance. In contrast, simulation-optimization methods match the available irrigation measurements to val-

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ues simulated with unsteady flow models, using an optimization algorithm to drive the solution. In principle, and because these methods account for both the conservation of mass and the flow dynamics, they can be used to estimate both infiltration and hydraulic resistance parameters. Within each of these categories, methods vary depending on mathematical details, among them the infiltration modeling approach.

For practitioners, selection of a parameter estimation method for a particular study depends on the flow variables that need to be, or can be, measured in the field, and the computational complexity. Methods that use limited data are preferable because measurements can be difficult, costly, and/or time-consuming to obtain. Likewise, users prefer estimation methods that rely on simple computations or methods that have been made available through user-friendly software applications. Typically, users judge the adequacy of the analysis based on how closely they can predict the available measurements with the estimated parameters. However, a lack of understanding of the limitations of parameter estimation methods can ultimately lead to unreliable results.

A primary factor that affects the reliability of a parameter estimation method is whether the system is observable and identifiable from the available data. In control engineering, a system is observable if pertinent system states can be inferred from a limited number of observations. Likewise, a system is identifiable if true parameters of the system can inferred from knowing the system states. Katopodes (1990) examined the application of these concepts to surface irrigation systems. He concluded that because of the non-linearity of the governing equations and because the effects of infiltration on the surface flow are difficult to discern separately from those of resistance, surface irrigation is partially observable. This conclusion was reached considering the possibility of observing infiltration depths at a number of locations and times, and assuming perfect observations. In practice, measurements are limited to surface flow variables (advance times, flow depths, runoff rate, and recession times), which further hampers our ability to characterize the evolution of infiltration. The practical consequence of the limited observability is that different combinations of parameters may satisfy the conditions of the estimation problem. These different solutions may predict similar infiltration volumes for times commensurate with the opportunity times used for estimation, but they may predict very differently when extrapolated. Not surprisingly, infiltration parameter estimates derived from measurements of advance time alone often misrepresent the infiltration process during the post-advance phase (Scaloppi et al., 1995; Esfandiari and Maheshwari, 1997; Gillies and Smith, 2005; Bautista et al., 2009a). Likewise, estimates derived using data from an entire irrigation event cannot be guaranteed to adequately represent infiltration for times longer than the duration of that event.

Further compromising the reliability of parameter estimation is the spatial and temporal variability of the infiltration and resistance processes, and of inputs to the estimation procedure, key among them inflow rate and field bottom slope. The estimation produces spatially averaged infiltration and roughness functions at a particular point in time for the evaluated irrigation event. Typically, data used for estimation are measured at the scale of an individual border or furrow, although procedures can be adapted to the scale of irrigation sets, if the appropriate data are available. In general, multiple evaluations are needed to characterize the potential range of infiltration and roughness conditions over a field and throughout the irrigation season. Because long-term soil management practices can alter the structure and hydraulic characteristics of soils, estimation methods that use limited data cannot capture the average behavior of the infiltration and resistance processes if the variability is substantial. Moreover, with few measurements, results can be expected to be very sensitive to outliers and measurement errors.

A final and fundamental factor that affects the reliability of parameter estimates is our limited understanding of infiltration and hydraulic resistance and, consequently, the inadequacies of the models used to represent these processes. Because this study is mostly concerned with infiltration, some comments will follow on those models.

Strelkoff et al. (2009b) reviewed models used to represent infiltration in surface irrigation. Historically, irrigation professionals have relied on empirical models, such as the Kostiakov equation:

$$A_z = K\tau^a \tag{1}$$

where A_z [L^2] is the infiltrated volume per unit length, τ [T] is the opportunity time, and K [L^2/T^a] and a [.] are parameters. Because equations like equation 1 predict infiltration as a function of opportunity time only, their solution is explicit. Empirical models do not account for initial and boundary conditions, and the parameters are specific to the conditions under which they were calibrated, including the geometry of the infiltrating surface. The use of empirical equations has been questioned, particularly when modeling furrow infiltration. In such cases, the infiltrating surface (and water pressure) can vary substantially with flow depth. Commonly used procedures for analyzing furrow infiltration assume that the process is independent of wetted perimeter effects, or that wetted perimeter effects can be accounted for in an average sense, thus ignoring the variations in flow depth along the field. Those assumptions have been shown to be justified under some soil conditions (Trout, 1992). However, other studies (Fangmeier and Ramsey, 1978) support the idea that furrow infiltration is better represented by a flow-depth dependent formulation.

Models based on porous media flow theory, such as the Richards equation or Green-Ampt equations (Warrick, 2003), depend on soil hydraulic properties, and they account for initial and boundary conditions and for the geometry of the infiltrating surface. Thus, predictions can be more easily extrapolated to times greater than and/or flow conditions different from those used for the determination of parameters. Practical use of these models in surface irrigation is only beginning, partly because of lack of familiarity with these approaches by users, partly because of the substantial computational and parameterization complexities (because the equations cannot be solved explicitly), and partly because porous media flow theory does not entirely explain infiltration under field conditions. A key problem is modeling flow through cracks and macropores, which can be predominant in many soils (Enciso-Medina et al., 1998; Clemmens and Bautista, 2009).

A practical approach for modeling flow-depth dependent furrow infiltration has been under development (Warrick et al., 2007; Bautista et al., 2014, 2016). That model was used in a simulation study to examine the implications of using different furrow infiltration modeling assumptions on the operation of furrow infiltration systems (Bautista, 2016). The ability of that model to represent infiltration under field conditions has not been examined.

A parameter estimation software component, named EVALUE, was recently developed (Bautista and Schlegel, 2017). This component has been incorporated into WinSRFR (Bautista et al., 2009b), a software package for the hydraulic analysis of surface irrigation systems. EVALUE uses a combination of volume balance techniques and unsteady flow simulation for the estimation of infiltration and hydraulic resistance parameters. This study evaluates the practical application of that component for the estimation of parameters of the above-described flow-depth dependent furrow infiltration model. The specific objectives are to:

- Test the proposed furrow infiltration modeling approach and associated estimation procedure with field data.
- Contrast furrow infiltration estimates derived with different empirical equations and with the proposed semi-physical model.
- Examine whether estimates of the hydraulic resistance parameter, specifically the Manning roughness coefficient, depend on the selected infiltration modeling approach.
- Provide guidance for the use of the proposed parameter estimation methods.

METHODOLOGY

INFILTRATION AND HYDRAULIC RESISTANCE MODELS

Part of the analyses presented herein assumes that infiltration volume per unit length (A_z [L^3/L]) is a function of opportunity time (τ) only, described by the general model (Bautista, 2016):

$$A_z = W_1\left(k\tau^a + b\tau\right) + W_2 c \tag{2}$$

where k [L/T^a] and a [.] are transient infiltration parameters, b [L/T] is the steady-state infiltration rate, c [L] is the instantaneous infiltration depth into soil macropores, and W_1 and W_2 are transverse lengths [L]. This equation can be used to model infiltration in basins or borders, in which case $W_1 = W_2$ = border width. With furrows, W_1 and W_2 can be either wetted perimeter or furrow spacing (F_S). This analysis assumes that that infiltration is independent of wetter perimeter effects, hence $W_1 = W_2 = F_S$.

For purposes of this analysis, it is also useful to consider variations of the empirical equation (eq. 2). Those variants are defined by setting one or more parameters to zero. When $b = c = 0$, equation 2 is simply the Kostiakov (Ko) equation (eq. 1). When only $c = 0$, the equation is referred to as the Kostiakov-Lewis (KoL) equation. When all parameters are non-zero, it is identified as the Modified Kostiakov (MKo) equation. In soils where macropore flow is dominant, several researchers have ignored the transient term ($k = 0$) and used only b and c to represent the infiltration process (Mailhol and Gonzalez, 1993; Grismer and Tod, 1994; Selle et al., 2011). For convenience, this version will be identified as the Mailhol-Gonzalez (MaG) equation.

The analysis also uses a flow-depth dependent, semi-empirical furrow infiltration model. Warrick et al. (2007) proposed an approximate furrow infiltration model, which they derived from disk infiltrometer theory. Based on modifications by Bautista et al. (2014), that model can be written as:

$$A_z(t) = z(t)WP + \frac{\gamma S_s^2 t}{\Delta\theta} \tag{3}$$

The first term on the right side of equation 3 is the product of one-dimensional infiltrated depth (z [L^3/L^2]) and the wetted perimeter (WP). The second term represents the lateral flow of water, which increases linearly with time. The latter term depends on the soil sorptivity (S_s [$L/T^{1/2}$]), the difference between the saturated (θ_s) and initial (θ_0) water content ($\Delta\theta$ [L/L]), and the calibration parameter (γ [.]), which is used to better match the approximate model results in comparison with infiltration calculations based on the two-dimensional Richards equation. Depending on soil, geometry, and boundary conditions, γ typically varies between about 0.6 and 1.0. In this study, equation 3 was implemented with z calculated with the Green-Ampt (GA) equation. Thus, it is identified as the Warrick-Green-Ampt (WGA) model. The GA equation can be written as (Warrick et al., 2005):

$$z = z_0 + K_s\left(t - t_0\right) + \Delta\theta\Delta h \cdot \ln\left(\frac{z + \Delta\theta\Delta h}{z_0 + \Delta\theta\Delta h}\right) \tag{4}$$

where z_0 is the infiltrated depth at time t_0; Δh is the difference between the water pressure at the infiltrating surface h (expressed as a depth) and the wetting front pressure head h_f (a negative quantity, expressed as a depth); K_s is the saturated hydraulic conductivity [L/T], and z and $\Delta\theta$ are as previously defined. Equation 4 is used to calculate z incrementally, assuming a step variation in the water depth h during the time interval $\Delta t_i = t_i - t_{i-1}$. Thus, at each time step, $t_0 = t_{i-1}$ and z_0 is equal to the value of z computed during the previous time step.

The GA equation, like the Richards equation, only models flow through a porous medium. In practice, a substantial volume of water can infiltrate through macropores and cracks. Several models of this process have been proposed, which vary in complexity (Ahuja et al., 1993; Enciso-Medina et al., 1998; Šimůnek et al., 2003). In this analysis, macropore flow is dealt with in a purely empirical manner by adding a macropore depth (volume per unit area) term (c_{GA}) to equation 4. Use of this term for both one-dimensional and two-dimensional infiltration rests on the assumptions that: (1) macropores fill instantaneously, (2) the infiltrated water does not bypass the root zone, and (3) the infiltration rate through the porous medium also decreases instantaneously as a function of the water added to the profile. The last assumption requires a time shift in the GA calculations (Clemmens and Bautista, 2009). An additional assumption required when applied to two-dimensional infiltration is that macropore flow occurs across the furrow spacing, in contrast with the flow described by equation 3, which depends on the wetted perimeter. After adding the contribution of c_{GA} and F_S, and with sorptivity expressed as a function of the GA parameters (Haverkamp et al., 1988; Warrick et al., 2007), equation 3 becomes:

$$A_z = z \cdot WP + c_{GA} FS + \gamma(2K_s \cdot \Delta h)t \tag{5}$$

Equation 3 was originally developed for a constant flow depth. Modifications for variable flow depth are described by Bautista et al. (2016). Those same modifications apply to equation 5.

EVALUE supports the estimation of coefficients for the Manning and Sayre-Albertson roughness models. This analysis uses only the Manning equation, which computes the friction slope (S_f) as:

$$S_f = \frac{v|v|}{R\left(c_u \frac{R^{1/6}}{n}\right)^2} \tag{6}$$

where v is the flow velocity, c_u is a units coefficient, R is the hydraulic radius, and n is the Manning roughness coefficient. Use of this equation in surface irrigation has been questioned (Maheshwari and McMahon, 1992) because it was developed from measurements in relatively deep, fully turbulent flows, while flows in irrigation are typically very shallow, slow, and may sometimes be a combination of turbulent and laminar flow. Moreover, equation 6 was developed considering boundary drag only, while hydraulic resistance in surface irrigation often combines channel boundary and vegetative drag effects. When calibrated from field data, the Manning equation has been shown to produce different values for the roughness coefficient n depending on flow rate and depth, even in a channel without vegetation (Maheshwari and McMahon, 1992).

Analysis with EVALUE

An EVALUE analysis is conducted iteratively. Volume balance is used to determine infiltration volumes V_z as a function of time and estimate the corresponding parameters. Simulation is used to correct inaccuracies of the volume balance analysis, validate the infiltration estimates, and calibrate the roughness parameter, if allowed by the available data. The volume balance analysis is adaptable to various irrigation evaluation data configurations, and thus to different evaluation strategies, including cases where the only available output measurements are advance times, and cases where the data set consists of a combination advance and recession times, runoff, and flow depth measurements. The application scans the data provided by the user and recommends times at which to calculate the volume balance. Alternatively, the user can suggest times for volume balance calculations, but those times have to be consistent with the available data.

Surface flow volumes needed for the volume balance analysis can be derived from measured flow depth hydrographs (i.e., from depth profiles calculated from the depth hydrographs) or estimated from hydraulic principles by assuming a known resistance function (Bautista and Schlegel, 2017). Which method is used depends on the available data. For simplicity, in the following discussion, these two approaches are identified as measured and hydraulically estimated surface volumes, respectively.

The solution to the infiltration estimation problem is found, in principle, by minimizing the sum-of-squares objective function (OF):

$$OF = \sum_{i=1}^{I}\left(V_z - V_z^*\right)^2 \tag{7}$$

where V_z^* are the predicted infiltration values, dependent on the unknown parameters, and I is the number of times at which the volume balance is calculated. The parameters are adjusted manually, with the aid of a graphical tool that displays the V_z, V_z^*, and OF values.

As noted earlier, simulation with the estimated infiltration function is used to correct inaccuracies in the volume balance analysis. Those inaccuracies are associated with shape factors used for the hydraulic estimation of surface volumes and for the integration of subsurface volumes (Bautista and Schlegel, 2017). The application quantifies the resulting errors and provides mechanisms for refining the shape factors. Because those factors depend on the infiltration function, a final set of infiltration parameters is found by repeatedly solving equation 7 and then adjusting the shape factors. The solution converges, generally, in a few iterations.

The EVALUE component can be used in combination with equations 2 and 5. With the latter, the estimation requires a two-step process. In the first step, initial estimates for infiltration and resistance are derived using equation 2. Those results are used to generate flow depth hydrographs via simulation. The simulated hydrographs are then used to solve equation 7, but with V_z^* calculated with equation 5 (Bautista and Schlegel, 2017).

When the volume balance analysis is calculated using measured surface volumes, the roughness parameter can be calibrated independently after estimating the infiltration function. This is done by minimizing the difference between measured and simulated flow depth hydrographs. As with infiltration, this part of the analysis is conducted with the aid of a graphical tool that displays the goodness-of-fit measures calculated at three user-selected values of the roughness coefficient. The following indicator was used for this part of the analysis:

$$\text{PBIAS} = 1/J \sum_{j=1}^{J} \text{PBIAS}_j \tag{8}$$

where $$\text{PBIAS}_j = \frac{\sum_{m=1}^{M}\left(y_l^{obs} - y_l^{sim}\right)}{\sum_{m=1}^{M}\left(y_l^{obs}\right)} \times 100 \tag{9}$$

PBIAS_j is the percent bias indicator (Gupta et al., 1999) calculated from the flow depths y measured at measurement station j, where M is the number of flow depth measurements at station j, and J is the number of measurement stations. This indicator measures the tendency of the simulated data to over- or underpredict the observations. With limited observations, as in these tests, PBIAS is less sensitive and easier to use than alternative indicators (e.g., RMSE, Nash-Sutcliffe efficiency) when determining the direction and magnitude of new values of n to be tested.

Depending on results, the user can narrow (or expand) the range of values to test and, ultimately, determine when a value that minimizes the differences has been found. When infiltration calculations depend on hydraulically estimated surface volumes, but a limited set of flow depth measurements is available, infiltration and resistance need to be estimated sequentially and iteratively. Infiltration is estimated first, based on a user-selected resistance equation and an initial guess for the resistance parameter. The available depth data are then used to adjust the resistance parameter, again using the graphical tool and simulation. This new estimate for resistance is used to calculate a new infiltration function, which in turn is used to adjust the resistance parameter. Experience suggests that two or three iterations of this process are generally needed.

Data Sets

Two groups of furrow evaluation data sets were selected for this analysis. The data are part of the compilation of free-draining furrow evaluations reported by Elliott (1980). The first group of tests is identified as "Benson Farm, Irrigation 3, Group 1, Furrows 1, 3, and 5." The second is identified as "Printz, Irrigation 4, Group 2, Furrows 1, 3, and 5." Table 1 summarizes pertinent variables. In these evaluations, field elevations, advance times, and recession times were measured at 25 m intervals, but recession was not measured to the end of the field. Runoff rate was measured up to near cutoff time. Partial flow depths were measured at 50 m intervals, and the readings do not cover the entire length of the field. Flow depth data are particular sparse for the Printz tests. However, the data can be used to determine the water surface profile at least at one time. Cross-sectional information was measured before and after the irrigation. Post-irrigation cross-section data were selected for the analysis and fit to a trapezoidal shape.

Determination of WGA Model Parameters

Parameter estimates were developed initially for equation 2, with both W_1 and W_2 set equal to the furrow spacing. Estimates were then developed for the parameters of the WGA equation (eq. 5) in combination with equation 4. There are six parameters to consider (K_s, θ_0, θ_s, h_f, c_{GA}, and γ), only two of which (K_s and c_{GA}) were determined from the evaluation data. Other parameters were determined as follows: an average initial volumetric water content θ_0 was determined from pre-irrigation gravimetric water content readings and bulk density data provided by Elliott (1980). The saturated water content (porosity) θ_s and h_f were determined from published data based on the reported soil textures (Elliott, 1980). The Benson soil was described as primarily clay loam, while the Printz soil consisted of a mixture of sands, loamy sand, sandy loam, and sandy clay loam. Sandy loam properties were assumed for the latter case. The θ_s and h_f values, given in table 1, were obtained from Rawls et al. (1983). Previous analyses, conducted with different soil textures, have shown that when the ponding depth h is constant, the parameter γ increases at small values of h (generally less than 5 cm) and then becomes relatively constant (Bautista et al., 2014, 2016). The latter study also showed that values of γ developed under variable h conditions are similar to those developed with constant h. Given that these values are often close to unity, γ was assumed to be embedded in the value of the calibrated K_s.

Results

Benson Tests

Volume Balance Analysis

Figure 1 depicts the infiltrated volumes computed with the volume balance analysis for each of the Benson furrows. Plot (a) shows the data as a function of time, and plot (b) shows the data as a function of distance. In plot (a), the label t_L identifies the final advance time of each test. Plots of V_z as a function of time and distance for a group of tests help identify infiltration patterns and anomalous results. In plot (a), differences between the $V_z(t)$ relationships developed for each furrow can be explained mostly as a function of the applied inflow rates (table 1), i.e., V_z grows more rapidly with time with larger inflow rates. Noticeable in all three $V_z(t)$ curves is the pronounced change in slope at t_L. While a dec-

Table 1. Geometric, irrigation, and soil data for the Benson and Printz evaluation data sets.

Parameter	Benson			Printz		
	Furrow 1	Furrow 3	Furrow 5	Furrow 1	Furrow 3	Furrow 5
Furrow length (m)	625	625	625	350	350	350
Bottom slope (S_0, m m^{-1})	0.0042	0.0042	0.0042	0.00248	0.00248	0.00248
Bottom width (F_{BW}, cm)	12	13.8	14.8	15.57	15.57	15.57
Side slope ($F_{H/V}$)	2	2.5	2.1	1.69	1.69	1.69
Average inflow rate (Q_0, L s^{-1})	1.8	2.8	2.3	3.1	3.2	3.8
Cutoff time (t_{co}, min)	590	589	589.5	171.5	173	171
Average applied depth (D_{app}, cm)	6.7	10.4	8.5	5.9	6.1	7.4
Final advance time (t_L, min)	379.5	217	245.5	98	105	111
Average opportunity time (t_{opp}, min)	420	493	474	132	130	127
Furrow spacing (F_S, cm)		152			152	
Soil texture		Clay loam			Sandy loam	
Initial volumetric water content (θ_0)		0.3			0.15	
Saturated water content (θ_s)		0.464			0.45	
Wetting front suction head (h_f, cm)		43			20	
Soil water deficit (cm)		6.7			2.23	

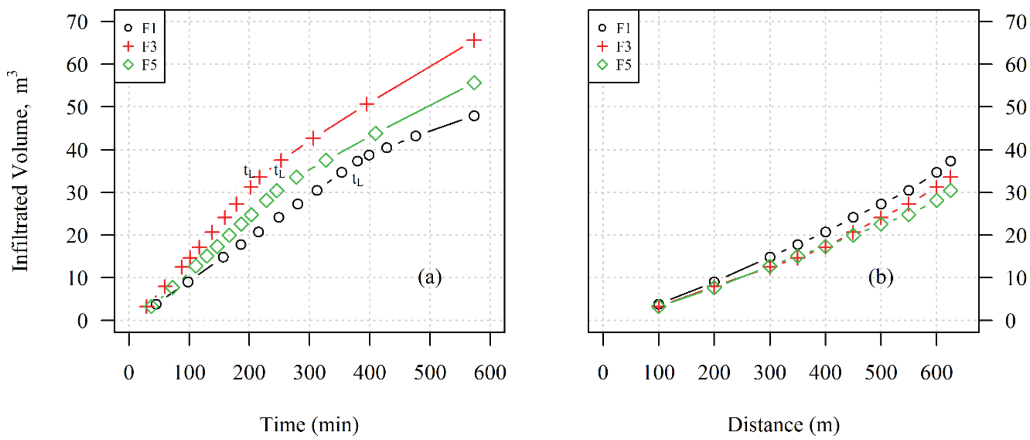

Figure 1. Volume balance results for the Benson furrows (F1 = furrow 1, F3 = furrow 3, and F5 = furrow 5).

rease in average infiltration rates over the entire furrow can always be expected after advance is complete, this effect can be expected to be relatively abrupt when macropores and cracks are present, which is often the case with clay loam soils. The curves exhibit slight slope differences during the post-advance phase, which again could be related to differences in inflow rate, and therefore wetted perimeter. V_z values vary smoothly when plotted against advance distance in plot (b), and those relationships showed smaller differences than when plotted against time. Thus, the data suggest relatively uniform soil and field bottom slope conditions along the furrows and among furrows. According to notes in the Elliott (1980) report, furrow 1 was least affected by compaction, and furrow 3 most affected. The $V_z(x)$ relationships in plot (b) support that observation for furrow 1, which infiltrated the largest volume during advance, but not for furrow 3, which infiltrated more water than furrow 5. Evidently, the impact of differential compaction in relation to infiltration variability is difficult to judge from this limited number of observations.

Estimation of Empirical Infiltration Functions

The proposed estimation procedure for flow-depth dependent infiltration parameters requires, first, calculating an infiltration function that is dependent only on opportunity time. This function is used to simulate the flow depth hydrographs needed to solve equation 7, with V_z^* given by equation 5. Of importance, then, is to examine the ability of different empirical infiltration equations to represent the infiltration process under a particular set of field conditions, and to assess the sensitivity of the WGA parameter estimates to the empirical infiltration equation used in the first part of the analysis.

The Benson data were used in combination with the Kostiakov (Ko), Kostiakov-Lewis (KoL), Modified Kostiakov (MoK), and Mailhol-Gonzalez (MaG) equations. Figure 2 displays the resulting infiltration functions. The parameter values are not important for purposes of this discussion; however, the MaG parameters will be discussed later when presenting the WGA results. The functions are presented as infiltrated depths (infiltration volume per unit length/furrow spacing).

These results illustrate the fundamental problem of non-uniqueness of estimated infiltration functions in surface irrigation. The functions generated for each furrow predict nearly the same infiltration depths, and therefore rates, for less than 450 min, which is approximately the average intake opportunity time of each test for the available data (table 1). As a result, the hydraulic performance computed with any of these functions is nearly the same. As an example, figures 3 illustrates the infiltration fraction (IF, the ratio of infiltrated to applied volume) for these tests. Differences in infiltration predicted with different functions for a furrow are fairly small in relation to differences in infiltration between furrows.

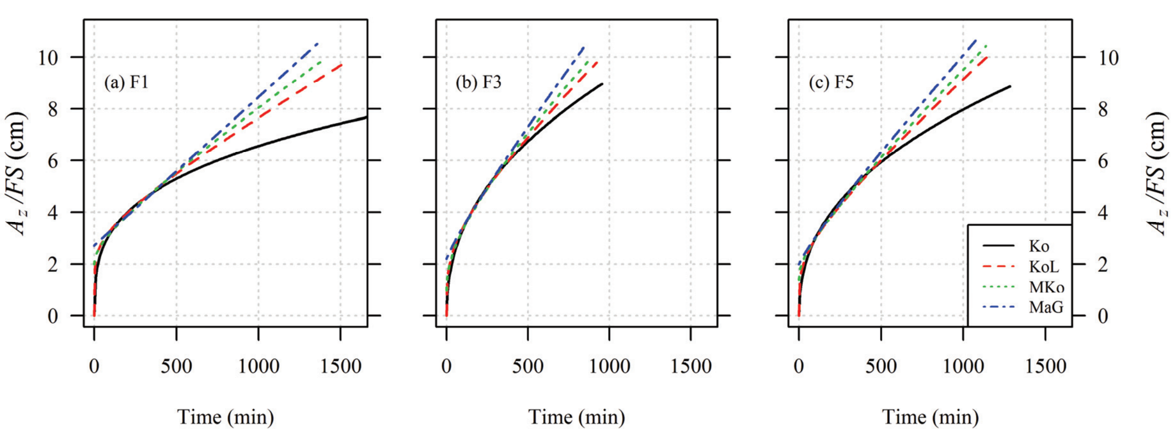

Figure 2. Empirical infiltration functions for the Benson furrows (F1 = furrow 1, F3 = furrow 3, and F5 = furrow 5).

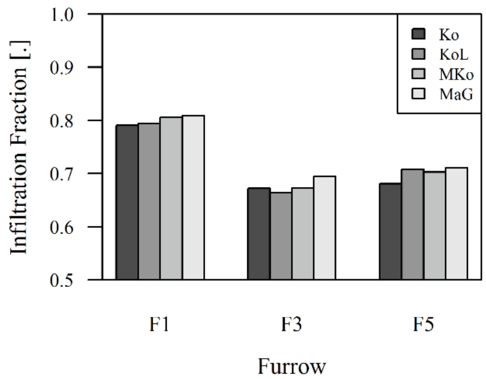

Figure 3. Infiltration fraction for the Benson furrows computed with different infiltration equations.

Several studies have developed recommendations for improving the design and operation of surface irrigation systems from field-measured infiltration functions (Lecina et al., 2005; Smith et al., 2005; Pereira et al. 2007; Sanchez et al., 2009; Clark et al., 2009; Schilardi et al., 2011). Most of those authors represented the infiltration process with the Ko or KoL equations, perhaps recognizing that different empirical models yield similar performance estimates. However, as indicated by the results in figure 2, judgement must be used when selecting an infiltration equation if the resulting functions are to be extrapolated. An infiltration process with very rapid changes in infiltration rate at short opportunity times, followed by gradual rate changes at longer times, as typically occurs with macroporous soils, is difficult to represent with both the Ko and KoL equations. While the assumption of an instantaneous initial infiltration may seem unrealistic, it provides a reasonable representation of the process. Evidence of the advantage of this approach and the limitations of the Ko and KoL equations is provided by the sum-of-squares (eq. 7) produced by the estimation for this field (fig. 4). As expected, the MKo equation, with four parameters, produced the best agreement between volume balance and predicted infiltration values for all furrows. Of note, however, is that the MaG equation, which depends only on a constant and a linear term, nearly matched those results. The *OF* values computed with the Ko equation were as much as ten times greater. The EVALUE component provides additional measures for comparing observed with simulated flow variables. Those indicators, which are not reported, show in fact that the simulation results generated with the MKo and MaG functions are very similar, except for the shape of the runoff hydrograph. With the latter function, the runoff rate rises to the steady-state value immediately after final advance. Other irrigation data sets are adequately described by the MaG equation, as will be shown later with the Printz data set.

Estimation of Manning Coefficient

The Benson furrows involve large differences in field elevation with distance (more than 2.5 m drop over the field length) and small flow depths (less than 4 cm). Small errors in any of those measurements and/or variations in the furrow cross-section, which was assumed uniform for these analyses, can translate into substantial differences between the measured and predicted flow depths, and perhaps large differences among the *n* values computed for different furrows. Despite these uncertainties, the predicted flow depths agreed reasonably well with the measured values with any of the infiltration equations. Figure 5 summarizes the PBIAS indicators for all analyses and the value of *n* computed for each furrow. These indicators point to slight differences in the flow depths with time and distance depending on the infiltration equation used. Nevertheless, the same *n* value was computed for each furrow. Moreover, nearly the same Manning *n* value was determined for all furrows, despite differences in the inflow rate. Thus, while infiltration characteristics vary substantially among furrows, roughness characteristics do not.

Estimation of WGA Function

The parameters of the WGA equation were developed from the flow depth hydrographs simulated with the infiltration functions of figure 2. Finding a solution was relatively easy. First, tests were conducted to assess the sensitivity of "known" parameters θ_s or h_f in comparison to K_s and c_{GA}. Those tests revealed that infiltration calculations are far more sensitive to K_s and c_{GA} than to θ_s or h_f. Thus, while estimates provided for θ_s or h_f may not be accurate, they were reasonable for purposes of these analyses. Second, the effect of K_s and c_{GA} on the V_z^* relationship was easy to discern. The macropore parameter shifts the V_z^* curve up and down relative to V_z (as in fig. 1a), whereas K_s changes the slope of the curve. The analysis was initialized using the Manning *n* values derived during the first stage of the analysis. Simulations

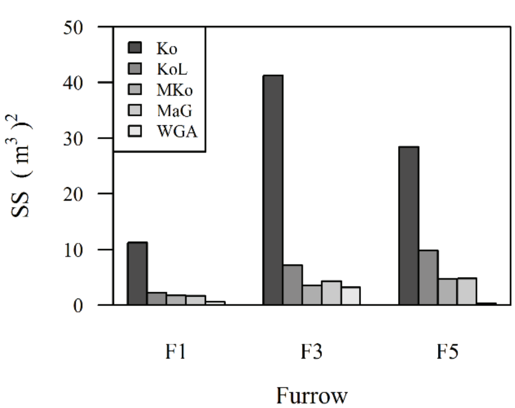

Figure 4. Objective function values for the Benson furrows computed with different infiltration equations.

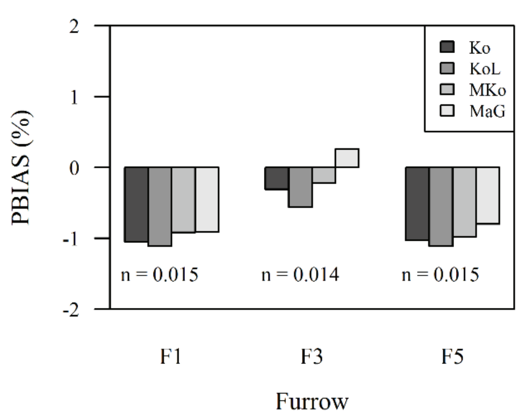

Figure 5. Estimation of Manning coefficients for the Benson furrows: parameters and PBIAS indicators.

were subsequently conducted with the estimated WGA functions, and the resulting flow depths were contrasted again with the measured values. The PBIAS values differed only slightly from those presented in figure 5 Thus, no further adjustments to the *n* values were required. With all scenarios, the WGA equation yielded *OF* (eq. 7) values that were smaller than those computed with the empirical functions, as illustrated in figure 4.

The resulting WGA functions, shown in figure 6, are nearly indistinguishable. In fact, the same solution was derived from the MKo and MaG functions. Because differences among solutions are minor in comparison with infiltration differences among furrows, any of the empirical equations considered here can be used to complete the first part of the estimation. Strong similarities between MaG and WGA functions can be discerned from comparing the respective curves in figures 2 and 6. Further evidence of the close relationship between these two sets of functions is provided by the parameters (fig. 7). Mailhol and Gonzalez (1993) suggested a relationship between the steady infiltration rate *b* and the saturated hydraulic conductivity K_s. However, as will be shown later with the Printz furrows, the estimated parameters of the WGA and MaG equations are not always that closely related. Of note is that the estimated K_s values were consistent with values reported in the literature for clay loam soils (between about 0.4 and 0.6 cm h^{-1}). Rawls et al. (1983) reported an average value of 0.23 cm h^{-1}, while the Soil Water Characteristic program (Saxton and Rawls, 2006) suggests values between about 0.2 and 0.76 cm h^{-1}. Thus, results are reasonable for the given soil. It is more difficult to comment on the estimated c_{GA} values, as there are few reports on macropore/crack volume in furrow-irrigated fields. Enciso-Medina et al. (1998) quantified crack volumes under such conditions, and their results showed substantial variability in relation to the values presented here. The c_{GA} values in figure 7 represent a substantial fraction of the final infiltration depth for these irrigation events: 45%, 30%, and 33% for furrows 1, 3, and 5, respectively. It is easy to show via simulation that advance times are sensitive to small changes in this parameter. For example, with furrow 1, increasing the estimated value of c_{GA} (2.5 cm) by 10% increases the final advance time by nearly 7%.

As previously stated, smaller objective function values were computed with the WGA equation than with any of the

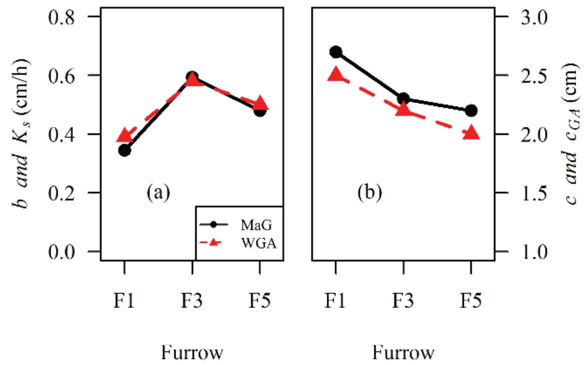

Figure 7. Infiltration parameters for the Benson furrows: Mailhol-Gonzalez and WGA equations.

empirical equations. This translated into an equal or better match between measured and predicted flow variables, particularly recession times. Predicted recession times were consistently shorter when computed with the empirical infiltration functions. Those times were more accurately predicted with the WGA functions, as infiltration slows with decreasing flow depth. Improvements were also noted in predicting the shape of the runoff hydrograph in comparison with the Mailhol-Gonzalez functions, as runoff rates predicted with the WGA functions exhibited a more gradual rise with time, closer to that predicted with the Modified Kostiakov functions.

Distribution Uniformity

Previous studies have shown that in graded free-draining furrows, the distribution uniformity will be overestimated if computed with an infiltration formulation that depends only on opportunity time, in comparison to an infiltration formulation that depends on the local and temporal variations in flow depth (Bautista, 2016). Figure 8 presents the distribution uniformity of the low-quarter computed with the Ko, KoL, MKo, MaG, and WGA functions. Clearly, differences among the purely empirical functions are minor, but results computed with the WGA functions are only slightly different. Again, infiltration variation among furrows is of greater consequence for determining the DUlq for the field than the infiltration modeling approach used. Two factors account for the small differences in the estimated DUlq between the WGA and empirical functions. First is the large amount of

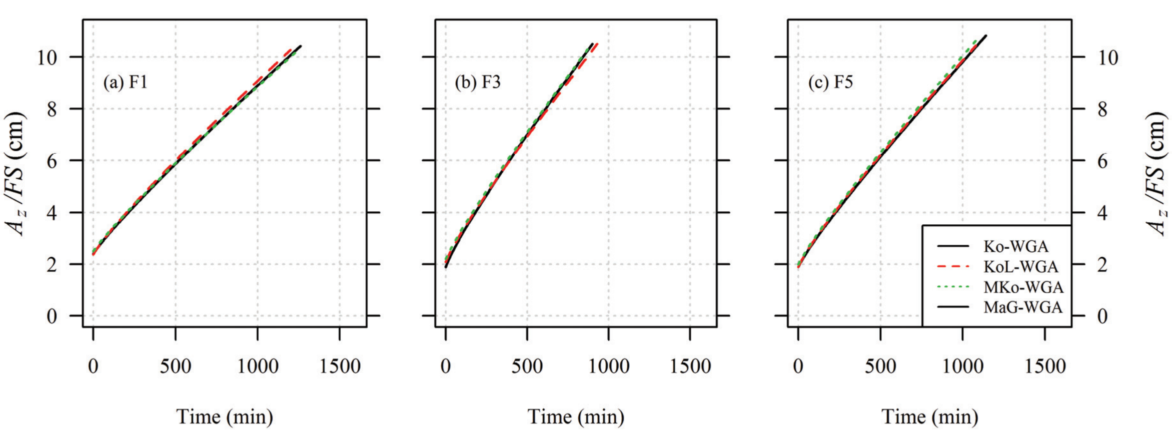

Figure 6. WGA infiltration functions for the Benson furrows: sensitivity to the empirical infiltration equation used in the first stage of the analysis.

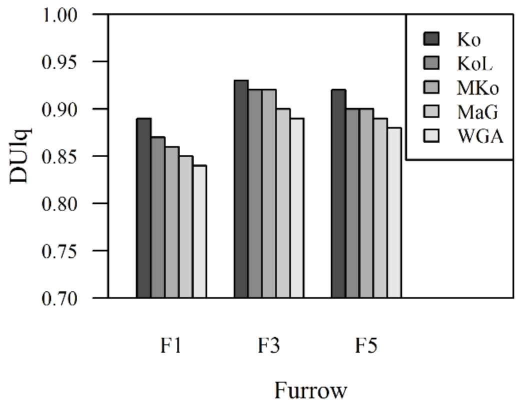

Figure 8. Distribution uniformity of the low-quarter computed with different infiltration equations for the Benson furrows.

water that infiltrates at very small opportunity times, presumably as macropore flow. The second factor is that under the surface flow conditions of these tests, with very shallow flow depths, variations in flow depths along the field do not translate into large variations in wetted perimeter. This minimizes the contribution of flow depth variations to the distribution of infiltrated water.

PRINTZ TESTS

In comparison with the Benson furrows, the volume balance analysis for the Printz data (fig. 9) revealed more subtle changes in furrow-averaged infiltration rates after advance was completed, mostly with furrow 1, as shown in plot (a). The effect is even less visible with furrows 3 and 5, perhaps because those furrows produced small runoff rates and volumes. However, the $V_z(x)$ curves, as shown in plot (b), suggest non-uniform field conditions, as indicated by a slope change at about $x = 300$ m for all furrows. Inspection of the available data revealed a reduction in the bottom slope in the last 50 m of the field (about half of the average field slope) and an inflow rate reduction before the stream reached the end of the field. Those two factors might explain why the infiltration volume per unit length increased near the end of the field. It is also possible that soil texture may have varied near the end of the field, but no data are available to examine this factor. This spatial irregularity of the volume balance data complicated the analysis, as will be discussed below. Another complicating factor was the runoff data. Because the runoff phase was short-lived, was measured for a relatively short time, and runoff rates were small, those data provided limited information about long-term infiltration rates.

With all furrows and all equations, the spatial irregularity of the data caused the predicted infiltration volumes to differ substantially from volume balance results at selected volume balance calculation times. Furthermore, although figure 9 does not provide strong evidence of macropore flow, minimizing the objective function proved difficult without including a macropore infiltration term. Hence, only results computed with the MoK and MaG equations (fig. 10) are

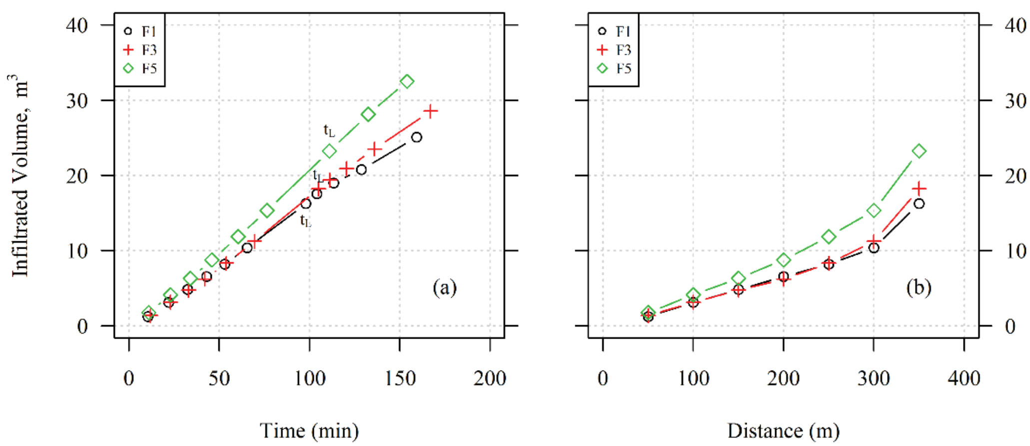

Figure 9. Volume balance results for the Printz furrows.

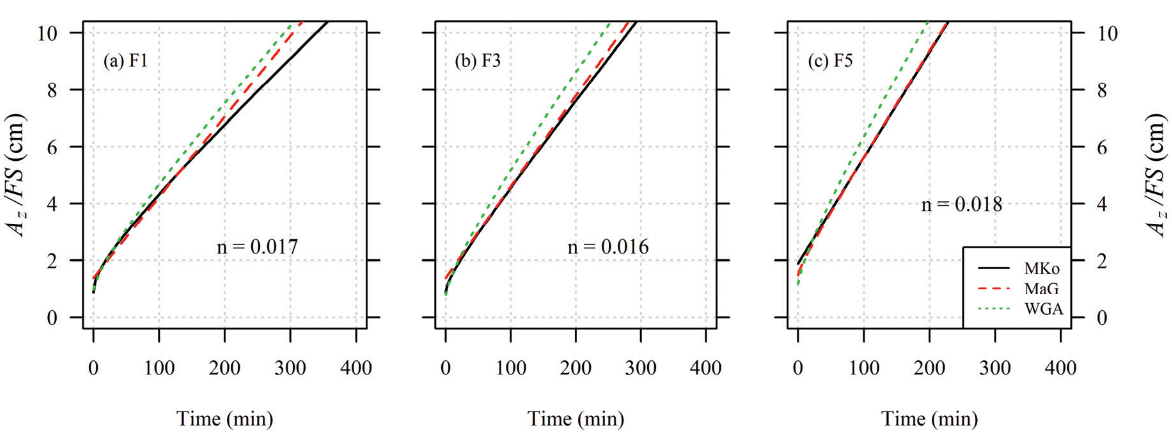

Figure 10. Modified Kostiakov, Mailhol-Gonzalez, and WGA infiltration functions for the Printz furrows.

presented in this section. The resulting functions predict very similar infiltration depths for times less than the average opportunity of the tests (table 1) but diverge slightly for longer times. As with the Benson furrows, there is substantial infiltration variability among the Printz furrows, measured in terms of the opportunity time for the average infiltrated depth of these tests (about 6.5 cm).

Figure 10 also shows the estimated Manning *n* values. This part of the analysis was conducted using fewer flow depth measurements than with the Benson furrows, but results still suggest that the estimates are not affected by the infiltration equation used in the analysis. As before, the Manning *n* estimates for the Printz furrows were smaller than the values generally recommended for bare furrows. Hydraulic resistance variations among the furrows seem, again, minor in comparison with infiltration variations.

The MKo and MaG infiltration functions of figure 10 were used to develop WGA parameter estimates. Those solutions were, again, easy to find using the reported initial water content and published values of θ_s and h_f for a sandy loam soil (Rawls et al., 1983). Unlike the Benson furrows, the MKo and MaG empirical functions produced slightly different WGA parameter estimates for the Printz furrows. However, both solutions reduced the *OF* values computed during the initial part of the analysis and produced some improvements in simulation, especially the prediction of recession times. The WGA functions derived from the MaG results are displayed in figure 10, while figure 11 compares the MaG and WGA parameters. The K_s estimates (between 2.65 and 3.73 cm h^{-1}) are consistent with values reported in the literature (Rawls et al., 1983; Saxton and Rawls, 2006). Elliott (1980) reported that furrows 1 and 3 were subject to greater compaction, and the K_s and c_{GA} values are consistent with that observation. In contrast with the results in figure 7, systematic differences between Ks and b, and between c_{GA} and c, can be noted. Why these parameter pairs were more closely related with the Benson furrows than with the Printz furrows cannot be explained at this time. One possible explanation is that, under the conditions of the Printz irrigation, infiltration rates may have not reached a steady state, which is what the *b* parameter represents. It is also possible that the agreement between the *b* and K_s parameters for the Benson furrows is coincidental.

The Printz furrows have a smaller bottom slope than the Benson furrows and were irrigated with larger inflow rates.

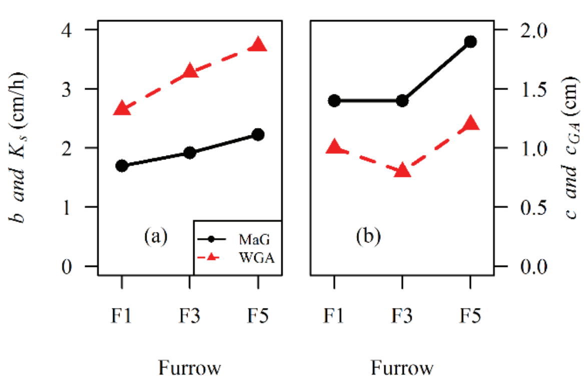

Figure 11. Infiltration parameters for the Printz furrows: Mailhol-Gonzales and WGA equations.

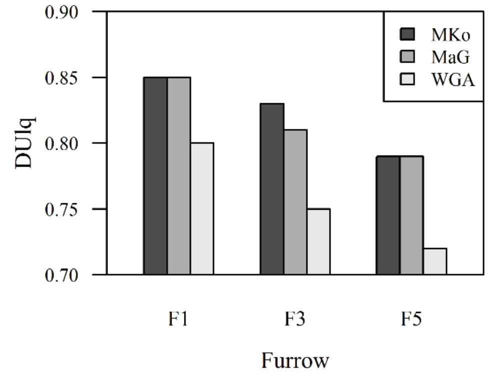

Figure 12. Distribution uniformity of the low-quarter computed with different infiltration equations for the Printz furrows.

Thus, flow depth variations are more extreme than in the previous set of tests as a function of time and distance. At the same time, with higher values of hydraulic conductivity, infiltration predictions are more responsive to variations in flow depth. As result, DUlq estimates were more sensitive to the infiltration modeling approach for the Printz furrows than for the Benson furrows. The average DUlq for the Printz furrows was about 0.83 if computed with the MKo equation but only 0.77 if computed with the WGA equation (fig. 12).

Discussion

An alternative approach for estimating the parameters of flow-depth dependent infiltration models in surface irrigation is to use simulation optimization, as done by Zerihun et al. (2005), Ram et al. (2012), and Bautista and Wallender (1993). The first two studies dealt with border irrigation and modeled infiltration with the one-dimensional Richards equation. The last study dealt with furrow irrigation but used a flow-depth dependent version of the Kostiakov-Lewis equation. A common concern in all of these studies was the convergence of the algorithm, including convergence to suboptimal solutions. This problem is also experienced when using infiltration equations that depend only on opportunity time. The estimation procedure presented herein avoids the convergence problem associated with optimization. Although the procedure can potentially produce suboptimal solutions relative to those produced with optimization, in these examples the inaccuracies were minor relative to the inherent variability of infiltration. All volume balance computations are robust, and the limited use of simulation makes the overall process computationally efficient. However, a reasonable understanding of the estimation problem and volume balance calculations is needed in order to use the approach effectively.

As stated in the introduction, users of parameter estimation methods for surface irrigation generally prefer methods that use limited data and that involve easy computation, or that perform the computation using a software application, with little user intervention. However, estimation is hampered by the limited observability of the irrigation process, the spatial and temporal variability of infiltration and estimation inputs, and modeling inadequacies. Future development of electronic sensors that can be used for irrigation evaluations will help address the first two problems. Still, solving a parameter estimation problem for a particular field will require testing alternative infiltration modeling approaches, identifying an approach that represents the process for the given data in a satisfactory manner, and trying to understand how the solution is affected by the limitations of the data. An objective in the development of the EVALUE component was to assist the user with these aspects of the estimation problem.

CONCLUSIONS

For the two sets of furrows presented in this study, infiltration was best described by the Modified Kostiakov equation, the Mailhol-Gonzalez equation, or the proposed WGA equation, all of which include a macropore flow term. Although the concept of a volume of water that infiltrates instantaneously is not realistic, it seems to provide a reasonable and simple description of the initial infiltration process. For the set of conditions studied here, both the Kostiakov and Kostiakov-Lewis equations have some limitations in modeling the rapid infiltration rates that take place in short times. This problem has been noted by the first author with other irrigation evaluation data sets.

The proposed WGA furrow infiltration modeling approach, which combines an approximation to the two-dimensional Richards equation (Warrick et al., 2007) with the Green-Ampt equation, and an empirical term to account for macropore flow, is a viable approach for modeling infiltration in furrow systems. For the conditions of these tests, this modeling produced comparable or slightly better simulation results than any of the empirical formulations considered in the analysis.

The proposed estimation procedure for the flow-depth dependent parameters of the WGA equation yielded consistent and reasonable results. Results are slightly sensitive to the empirical infiltration equation used in the first stage of the analysis. For these two sets of examples, the Mailhol-Gonzalez equation provided the simplest mechanism for conducting the initial part of the analysis and led to the same or nearly the same WGA parameter estimates as the Modified Kostiakov equation.

For these groups of tests, Manning *n* estimates were not affected by the infiltration equation used in the analysis. In addition, roughness estimates were fairly consistent for each field, despite differences in the inflow rate applied to furrows within each test group. Additional studies are needed to further evaluate the variability of hydraulic resistance in a furrow-irrigated field.

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