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Calibration of effective soil hydraulic parameters of heterogeneous soil profiles

R.K. Jhorar[a,*], J.C. van Dam[b], W.G.M. Bastiaanssen[c], R.A. Feddes[b]

[a]*Department of Soil and Water Engineering, College of Agricultural Engineering and Technology, Chaudhary Charan Singh Haryana Agricultural University, 125 004 Hisar, India*
[b]*Department of Water Resources, Wageningen Agricultural University, Nieuwe Kanaal 11, NL-6709 PA Wageningen, The Netherlands*
[c]*Water Watch, Generaal Foulkesweg 28, 6703 BS Wageningen, The Netherlands*

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Abstract

Distributed hydrological models are useful tools to analyse the performance of irrigation systems at different levels. For the successful application of these models, it is imperative that effective soil hydraulic parameters at the scale of model application are known. The majority of previous studies to define effective soil hydraulic parameters have considered only horizontal spatial variability of the parameters while neglecting textural layering at different spatial locations. In this paper, numerical experiments are conducted for seven vertical heterogeneous soil profiles (containing 4–5 soil layers) to generate different water balance components. Thereafter, information on evapotranspiration fluxes and water storage in the root zone profile is inversely used to identify effective soil hydraulic parameters. The aim is to assess whether effective soil hydraulic parameters can be assigned to vertically heterogeneous soil profiles. The performance of inversely identified soil hydraulic parameters is evaluated by their ability to reproduce the different components of water balance. Results showed that the evapotranspiration fluxes are sufficient to inversely identify soil hydraulic parameters for heterogeneous soil profiles under deep water table conditions and significant moisture stress. The identified soil hydraulic parameters are suitable to predict water balance components. However, appropriate formulation of soil evaporation simulation is very important if the surface soil layers have deviating soil hydraulic properties. Results also showed that general information on the textural layering of the area is an important input to inversely identify effective soil hydraulic parameters using evapotranspiration fluxes.

Keywords: Heterogeneity; Soil profiles; Water balance; Effective parameters; Evapotranspiration; Inverse problem

1. Introduction

There is an increasing interest to analyze the performance of irrigation systems at field as well as scheme level (Agarwal and Roest, 1996; Molden et al., 1998). Distributed hydrological models that compute water balance components are useful tools for such

* Corresponding author. Fax: +91-1662-234952.
E-mail addresses: jhorar@yahoo.com (R.K. Jhorar), jos.vandam@wur.nl (J.C. van Dam), w.bastiaanssen@waterwatch.nl (W.G.M. Bastiaanssen), reinder.feddes@wur.nl (R.A. Feddes).

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analysis (Droogers and Kite, 1999). However, most of the available models are basically point models (e.g. D'Urso et al., 1999; Droogers et al., 2000) and simulate different fluxes in one-dimension (vertical) only. In principle, a point simulation can only be representative of an areal extent if the involved area is homogeneous in all its components. However, homogeneity in all aspects never occurs in reality. This means that representative model input parameters should be identified at the scale of model application. A serious limitation of current model applications is the non-availability of representative input parameters (van Dam, 2000).

Hydrological simulation models utilize a set of parameters and inputs that are specific to the location being simulated. Computed water balance components are quite sensitive to soil hydraulic parameters. Therefore, accurate quantification of soil hydraulic parameters is essential to model hydrological processes. At most sites, soil hydraulic parameters have large variability not only in horizontal direction but also in the vertical direction. For example, Ahuja et al. (1984) observed different scaling factors for saturated hydraulic conductivity and wetting front pressure head at different depths for three silt loam soils. One approach to estimate the large scale mean behaviour of an unsaturated flow system is to couple the stochastic unsaturated flow theory developed by Mantoglou and Gelhar (1987a,b,c) with appropriate numerical simulation model (Jensen and Mantoglou, 1992).

In general, it is not feasible to model the heterogeneity deterministically as this would require too much data and computational effort (van Dam and Feddes, 1996). Alternatively, one could interpret the soil as an equivalent homogeneous medium with average (effective) hydraulic properties that predict the average flow and transport behaviour of the system (Wildenschild and Jensen, 1999). For instance, when studying the performance of an irrigation system at the canal command of distributary level, we are not directly interested in details of the internal variability. Therefore, it is very important to determine representative soil hydraulic parameters at the scale of model application. There are only, operationally available, in-direct methods to determine representative soil hydraulic parameters at larger scales.

Indirect methods such as pedotransfer functions (PTFs) (Saxton et al., 1986) and scaling techniques (Raats, 1990) are often suggested to derive area representative soil hydraulic parameters (Kabat et al., 1997; Batjes, 1996). PTFs relate the soil hydraulic parameters to more easily available soil properties through regression equations (Wösten and van Genuchten, 1988) and have the limitation of being site specific. In principle, PTFs must be derived from large profile data sets (Reynolds et al., 2000) and are applicable for similar conditions only. Another frequently used technique to account for spatial variability is scaling. Scaling can also be used to regionalize one-dimensional simulation models (Kabat et al., 1997). In the scaling procedure, a mean curve is fitted through the scaled hydraulic data (Clausnitzer et al., 1992). Although these techniques are useful, intensive direct field measurements are required. This restricts the applicability of PTFs or scaling techniques to derive area representative soil hydraulic parameters. It may not be feasible to obtain enough direct measurements across an area to adequately reflect the soil spatial heterogeneity. Moreover, there appears as yet, no simple way to predict a field *effective* set of soil hydraulic parameters on the basis of the sample measurements of soil parameters (Smith and Diekkrüger, 1996).

Alternatively, inverse modelling is a promising method to derive effective soil hydraulic parameters. Rapid increase in processor calculation speed, development of efficient optimization algorithms and availability of areal fluxes from remote sensing techniques have created the possibility to determine area effective soil hydraulic parameters of distributed hydrological models by inverse techniques (Schmugge et al., 1992; Burke et al., 1998; Feddes et al., 1993a). However, successful application of the inverse modelling technique requires an adequate physical description of the system being simulated. Any error in the physical-mathematical model concept, including the interrelated processes, will affect the effective parameters. Therefore, inversely estimated parameters are effective only within the employed modelling concept. Nevertheless, in the past few years, applications of the inverse method to estimate soil hydraulic parameters have increased rapidly (see Hopmans and Simunek, 1999). Assuming that a given physical-mathematical model concept is an acceptable representation of the real system, the inverse approach would results in more representative parameter estimates. This is due to the fact that the inverse approach is based on experimental data that convey explicit information about the combined heterogeneous system behaviour (Wildenschild and Jensen, 1999).

Various attempts have been made to derive effective soil hydraulic parameters using the inverse approach (Feddes et al., 1993b; Wildenschild and Jensen, 1999; Jhorar et al., 2002). Basically, these studies have been carried out to demonstrate that effective soil hydraulic parameters exists/or can be derived for spatially variable hydraulic parameters. In the studies cited above, the concept of effective parameters has been tested on data representing vertically homogeneous soil profiles. For example, Feddes et al. (1993b) derived effective soil hydraulic parameters assuming a hypothetical watershed area consisting of 32 parallel blocks of spatially variable but vertically homogeneous soil profiles. In fact, even most of the studies reported to assess the impact of soil heterogeneity on field water balance components, whether using numerical-stochastic experiments (Kim et al., 1997) or laboratory-numerical experiments (Wildenschild and Jensen, 1999), with rare exceptions (Li et al., 2001), assumes vertical soil homogeneity and deals with only horizontal spatial variability. However, natural soils are hardly ever uniform or homogeneous in the vertical direction (Braun and Kruijne, 1994).

The fact that soil layering affects field water and solute transport is well known (Feyen et al., 1998). Li et al. (2001) demonstrated that the spatial variation of soil textural profile structures has a very strong influence on the field water balance and cautioned that soil hydraulic parameters derived from only a few soil profiles are not representative of the quantitative characteristics of the regional field water balance. It is not yet clear whether effective soil hydraulic parameters can be derived for heterogeneous soil profiles. Therefore, this paper examines the possibility of deriving effective soil hydraulic parameters for heterogeneous soil profiles.

2. Methodology

The possibility of deriving effective soil hydraulic functions of heterogeneous soil profiles, by inverse modelling of actual evapotranspiration fluxes ET_a and average moisture content in the root zone θ_{rz}, is tested through numerical experiments. Forward simulations were carried out with the simulation model SWAP (van Dam et al., 1997) for different heterogeneous soil profiles to generate ET_a and θ_{rz} as if these were available from independent measurements. Forward SWAP simulation results on T_a and E_a between day number 100 and 160 were used to get ET_a fluxes for the inverse modelling exercise. The modelled moisture content at each node in the 120 cm soil profile was used to calculate θ_{rz} in the root zone (120 cm). Thereafter, the parameters estimation program PEST (Doherty et al., 1995) is used to inversely identify different parameters of the soil hydraulic function model proposed by van Genuchten (1980).

2.1. Data set on heterogeneous soil profiles

Laboratory measurements on soil matric pressure head h–gravimetric water content pair, bulk density, particle density and saturated hydraulic conductivity as reported by Sood (1969) for seven soil profiles (Fig. 1) were used. Sood (1969) used following methodology for different laboratory measurements: constant head method for saturated hydraulic conductivity of disturbed soil samples, Richard's pressure plate extractor for moisture retained at 1/3 and 1.0 atmospheric tension, sand column to determine moisture retained at 1/100 and 1/1000 atmospheric tensions, Richard's pressure membrane extractor for moisture retained at 5, 10 and 15 atmospheric tensions. The soil texture class at the surface is mainly sand and ranges from sandy loam to sandy clay loam in deeper horizons. The gravimetric soil water content was multiplied by the soil bulk density to obtain the volumetric water content, θ. The seven sites belong to the command area of Kheri distributory, a part of the Bhakra Irrigation system in Haryana, India. The Kheri distributory commands an area of about 22,800 ha. The majority of the soils in the area are classified as sandy loam, though the surface horizons are mostly sandy in texture and the subsurface horizons vary from loamy sand to silty clay. Further details are reported in Sood (1969).

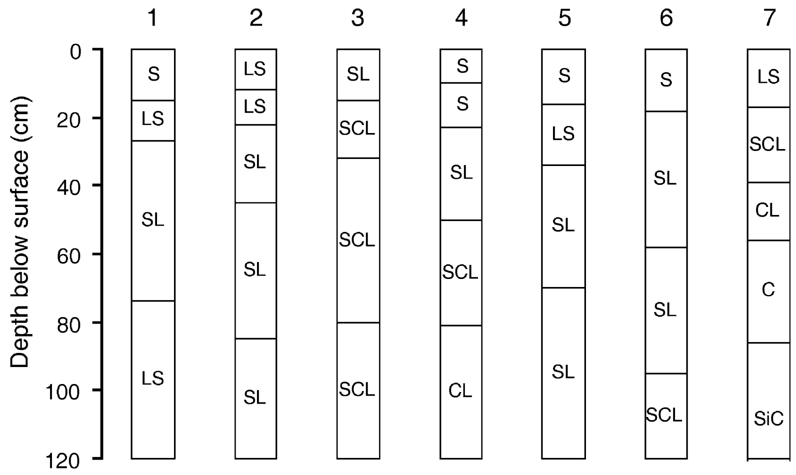

Fig. 1. Textural information of the seven soil profiles used during forward simulations. The symbol S stands for sand or sandy, Si for silty, C for clay and L for loam or loamy. Accordingly SL means sandy loam; LS means loamy sand and so on.

The following form of retention function (van Genuchten, 1980) was fitted to the measured $h - \theta$:

$$\theta = \theta_r + [\theta_s - \theta_r][1 + (\alpha h)^n]^{-m} \tag{1}$$

where θ_s and θ_r are, respectively, saturated and residual water content (L^3L^{-3}), and α (L^{-1}), n, m ($= 1 - 1/n$) are empirical shape factors.

Eq. (1) was fitted with the parameters estimation program PEST. Like Schaap and Leij (2000), the following constraints were imposed during the optimisation: $0.0 < \theta_r < 0.3\ \mathrm{cm^3\ cm^{-3}}$; $0.6\phi < \theta_s < \phi$ (where ϕ is the total porosity defined as 1-bulk density/particle density); $0.0001 < \alpha < 1.000\ \mathrm{cm^{-1}}$; $1.0001 < n < 10$. The resulting fitted parameters are shown in Table 1.

The following form of hydraulic conductivity function (van Genuchten, 1980) is used in SWAP:

$$k = k_s S_e^{\lambda}[1 - (1 - S_e^{1/m})^m]^2 \tag{2}$$

where k and k_s are the unsaturated and saturated hydraulic conductivity (LT^{-1}), respectively, λ is an empirical shape factor and S_e is the relative saturation defined as $(\theta - \theta_r)/(\theta_s - \theta_r)$.

The parameters of Eq. (2) were not fitted. k_s values were fixed at the measured value of saturated hydraulic conductivity (Table 1) and λ was fixed at -1.0 (Schaap and Leij, 2000).

2.2. Forward simulation

The basis for the numerical experiments conducted in this study is the one-dimensional saturated–unsaturated soil water flow model SWAP (van Dam et al., 1997). SWAP is based on the finite difference solution of Richards' equation extended with a sink term to account for root water uptake. Daily model outputs includes simulated actual evaporation E_a, actual transpiration T_a, flow across the bottom of soil profile and moisture distribution in the soil profile. T_a is simulated following Feddes approach (Feddes et al., 1978). In case of a wet soil, actual soil evaporation rate, E_a (mm d^{-1}), is determined by the atmospheric demands and equals potential evaporation E_p (mm d^{-1}). When the soil dries out, the soil hydraulic conductivity decreases and E_a is controlled by the maximum possible soil water flux E_{max} (mm d^{-1}) in the top soil. In SWAP, E_{max} is computed according to Darcy's law and E_a is set equal to minimum of E_p and E_{max}. However, there is one serious limitation of the E_{max} procedure. The E_{max} depends on the soil hydraulic functions of the top soil compartments. Still it is not clear to which extent the soil hydraulic functions, that usually represent a top layer of a few decimetre, are valid for the top few centimetre of soil, which are subject to splashing rain, dry crust formation, root extension, various cultivation practices (van Dam, 2000) and wind and water erosion or sediment deposition. Therefore, SWAP has the option

Table 1
van Genuchten model parameters for 120 cm soil depth for seven location in the Kheri distributary of Bhakra Irrigation system, Haryana, India. Except k_s, all the parameters were fitted as described in Section 2.2

Soil depth (cm)	θ_s	θ_r	α (cm^{-1})	n	k_s (10^{-3} cm s^{-1})
Site 1					
0–15	0.45	0.03	0.0771	1.66	1.61
15–27	0.46	0.07	0.0564	1.62	1.38
27–74	0.47	0.07	0.0465	1.67	1.05
74–120	0.46	0.08	0.0473	1.74	1.03
Site 2					
0–12	0.45	0.05	0.0330	1.85	0.93
12–22	0.46	0.05	0.0280	1.84	1.14
22–45	0.42	0.10	0.0164	1.98	0.87
45–85	0.41	0.10	0.0118	1.86	0.84
85–120	0.36	0.10	0.0111	1.64	0.44
Site 3					
0–15	0.46	0.03	0.0562	1.85	1.11
15–32	0.41	0.12	0.0166	1.75	0.62
32–80	0.40	0.07	0.0257	1.71	0.33
80–120	0.39	0.13	0.0070	1.70	0.37
Site 4					
0–10	0.43	0.03	0.0559	1.81	2.13
10–23	0.41	0.03	0.0298	2.06	2.56
23–50	0.38	0.08	0.0192	1.70	0.89
50–81	0.38	0.11	0.0149	1.54	0.31
81–120	0.39	0.01	0.0014	1.29	0.10
Site 5					
0–16	0.45	0.04	0.0361	2.07	2.25
16–34	0.44	0.06	0.0275	1.73	1.61
34–70	0.47	0.07	0.0346	1.63	1.17
70–120	0.43	0.08	0.0212	1.65	0.99
Site 6					
0–18	0.45	0.03	0.0667	1.83	1.88
18–58	0.42	0.05	0.0406	1.44	1.15
58–95	0.42	0.09	0.0160	1.54	0.55
95–120	0.37	0.09	0.0059	1.51	0.23
Site 7					
0–17	0.46	0.04	0.0852	1.47	1.21
17–39	0.38	0.00	0.0074	1.22	0.28
39–56	0.33	0.04	0.0009	1.25	0.29
56–86	0.36	0.18	0.0011	1.67	0.55
86–120	0.41	0.00	0.0063	1.21	0.21

to calculate evaporation according to empirical functions, E_{emp} (mm d^{-1}), of Black et al. (1969) or Boesten and Stroosnijder (1986). SWAP determine E_a by taking the minimum value of E_p, E_{max} and, if selected by the user, E_{emp}.

Forward SWAP simulation are carried out for a cotton crop for the seven soil profiles assuming deep groundwater situation by specifying free drainage as the lower boundary condition. All simulations start from the assumed date of sowing (26 June) of cotton. A soil matric pressure head corresponding to -200 cm ($h = pF2.3$) was specified as initial condition for all the soil profiles. Meteorological data from the Haryana Agricultural University Hisar (India), representing an arid climate, are used. The sink term variables required for reduction in ET_a due to moisture stress (Feddes et al., 1978) were calibrated for a cotton crop grown in a field experiment at Sirsa, India (Bastiaanssen et al., 1996). Simulations cover the growing season of a cotton crop for 160 days. Five post sown irrigations, each 60 mm, are specified at day number 51, 72, 97, 118 and 143, in which day number 1 represents the day of sowing.

First, the inverse approach is applied to identify effective soil hydraulic parameters for the individual soil profiles. Thereafter, an attempt is made to derive area effective parameters. To investigate the ability of deriving the area effective soil hydraulic parameters, information on areal fluxes is required. In practice such data can be derived using satellite images. Low resolution satellites such as NOAA-AVHRR and TERRA-MODIS can provide daily ET fluxes at the 1 km scale if the sky is clear. Under Indian conditions, such a scale often involves a mixture of soil and crops. In accordance with the aim of the present study to test the possibility of defining heterogeneous soil profiles by effective parameters, the effect of crop variability was ignored. The reason for exclusion of crop heterogeneity along with a procedure for its inclusion are further elaborated in Section 4 on general discussion. We only consider a mixture of soils while a uniform crop (cotton) is assumed everywhere. As a follow-up of this study in future, we intent to attempt and prove the feasibility of proposed technique under actual field conditions. For the present study, we consider that the whole of the Kheri distributary area may be represented by a collection of n sub-areas. In our case each sub-area is represented by either of the seven soil profiles. Each sub-area occupies a certain fraction of the total area. For each sub-area, the fluxes are known from the forward simulations. The areal measurements on ET_a

are then obtained by the following aggregation rule:

$$\mathrm{ET}_a^*(t) = \sum_{i=1}^{n} \mathrm{ET}_a(i,t)F_i \tag{3}$$

where $\mathrm{ET}_a^*(t)$ is the estimated areal actual evapotranspiration on day t, n is the number of sub-areas (seven in our case) in the total area, $\mathrm{ET}_a(i,t)$ is the corresponding (forward simulated) ET_a for the sub-area i and day t, and F_i is the fraction of total area represented by the sub-area i.

2.3. Parameter estimation procedure

The ET_a and θ_{rz} observations as generated from forward simulations are employed as input data to the numerical inversion problem. An overview of the parameters estimation procedure is shown in Fig. 2. PEST runs the SWAP with an initial guess of the parameters, compares the model results with observations, adjusts selected parameters using an optimization algorithm and runs the model again. The procedure of adjusting selected parameters continues until the difference between the model results and observations or the number of iterations, meets a preset criteria.

Let $\mathrm{ET}_a(b,t_i)$ and $\theta_{rz}(b,t_i)$ be the numerically calculated values of ET_a and θ_{rz}, respectively, at time t_i corresponding to a trial vector of selected parameter values $\{b\}$, where $\{b\}$ is the n-dimensional vector containing the parameters that are optimized simultaneously. The inverse problem is then to find

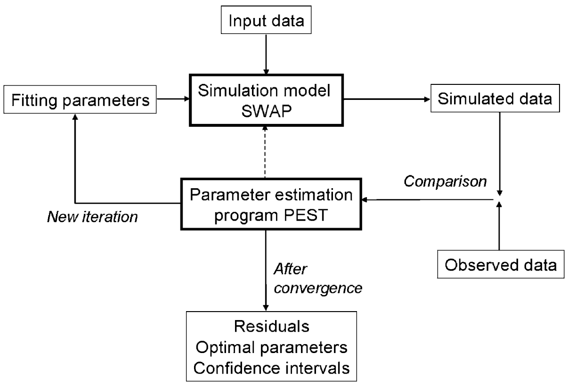

Fig. 2. Overview of the parameter estimation procedure employed using PEST and SWAP.

an optimum combination of parameters $\{b^0\}$ that minimizes the following weighted least square objective function:

$$O(b) = \sum[(w_i(\mathrm{ET}_a(t_i) - \mathrm{ET}_a(t_i,b)))^2 + (v_i(\theta_{rz}(t_i) - \theta_{rz}(t_i,b)))^2] \tag{4}$$

where w_i and v_i are the weighting factors accounting for data type as well as data point. We assigned weights to different observations (ET or θ) as inversely proportional to the magnitude. Assignment of the weight in this way implies that every observation have equal contribution to the objective function, irrespective of its magnitude (Jhorar et al., 2002).

The possibility of finding $\{b^0\}$ using only ET_a data (setting $v_i = 0$) as well as using both ET_a and θ_{rz} in the objective function was explored. Accordingly Eq. (4) will be referred as ET-based objective function when $v_i = 0$, and ET $-\ \theta$ based objective function when both w_i and v_i are non-zero.

We use ET_a or ET_a and θ_{rz} observations for 12 selected days ($t = 100$, 105, 110, 115, 120, 125, 130, 135, 140, 145, 150 and 159) as input to the objective function (Eq. (2)). In the inverse procedure, different sets of soil hydraulic input parameters were selected for optimization. Except for the optimization runs when the effect of initial guess of different parameters on the inverse results was investigated, same values of initial guess of different VG model parameters was specified for different parameter sets. The initial values of VG model parameters as specified during inverse optimizations are: $\alpha = 0.01\ \mathrm{cm}^{-1}$, $n = 1.5$, $\theta_s = 0.40\ \mathrm{cm}^3\ \mathrm{cm}^{-3}$, $\theta_r = 0.00\ \mathrm{cm}^3\ \mathrm{cm}^{-3}$, and $k_s = 1.16 \times 10^{-3}\ \mathrm{cm\ s}^{-1}$. The shape factor λ was fixed at a known value of -1.0.

2.4. Evaluation criteria

Traditionally, reliability of estimated parameters is evaluated based on statistical properties (e.g. bias, standard deviation) of fitted values (Wagner and Gorelick, 1986). However, these parameter estimates may be meaningless if the model fails to reliably reproduce salient features of particular interest. The ultimate objective of this study is to derive soil hydraulic functions appropriate to develop and test alternative water management practices in an irrigation context. A water budget for unsaturated zone consists of principal inflows and outflows for the soil depth of interest and the resulting change in water storage (ΔS). For irrigated arid and semi-arid regions with deep groundwater table, the principal inflows are rainfall (R), irrigation (I) and the principal outflows are, if there is no runoff, $\mathrm{ET_a}$ and deep percolation (Q). The water balance for such areas can be described by:

$$\Delta S = R + I - \mathrm{ET_a} - Q \tag{5}$$

Fundamental to the adopted inverse procedure is that the VG model parameters are fitted in such a way that the ability of the model to reproduce $\mathrm{ET_a}$ and/or θ_{rz} is optimised. It is well recognised that the fitted parameters do not have a strict physical meaning. A possible correlation between them means that many combinations of the parameters could fit the data (in our case $\mathrm{ET_a}$) equally well (Snow and Bond, 1998), so casting doubt on the values of simultaneously optimised parameters. Therefore, it is important to know how fitted VG model parameters will reproduce other water balance components such as ΔS and Q. Moreover, when representing a multi-layer soil profile with a single layer having equivalent parameters, identification of precise parameters values makes no sense. Accordingly, we do not intend to derive precise parameter values rather we will derive effective soil hydraulic parameters which can be reliably used for water balance computations. It may also be potentially incorrect to use inversely estimated parameters for conditions different from those present in the original inversion experiment (Hollenbeck and Jensen, 1998). Therefore, we evaluate the performance of fitted soil hydraulic parameters by studying the overall hydrological consequences of these parameters for a different irrigation regime than that was used during parameter optimisation.

The hydrological behaviour of the fitted parameters was tested through a verification numerical experiment by simulating seasonal water balance components of cotton crop. Care was taken to minimise any discrepancies, resulting due to initial conditions, in the simulated hydrological behaviour, particularly deep drainage. The initial profile condition specified for each verification experiment was such that for zero flux condition at the soil surface, the cumulative drainage past 120 cm depth was just negligible ($= 0.009$ cm) for a period of 160 days. Thereafter simulations were performed for cotton crop by specifying 20 cm irrigation on day 1 and 5 post sown irrigation each of 10 cm (instead of 6 cm during inverse optimisation). Seasonal simulated water balance components (ET, ΔS and Q) for the reference and fitted soil hydraulic functions are compared to evaluate the performance of the inversely identified parameters.

3. Results and discussion

In the following paragraphs, different water balance components are referred as ‘simulated’ for the simulated values based on inversely identified parameters and as ‘reference’ for the simulated values based on known parameters (forward simulations). Results of inverse procedure are first presented for individual soil profiles and then for the area effective soil profile.

3.1. Individual soil profiles

Different combinations of measurements data, number of soil layers, E_a simulation and number of fitted parameters (Table 2) were selected to study their influence on the hydrological behaviour of the inversely identified soil hydraulic parameters.

In Case 1 we use the ET-based form of the objective function. It is used to optimize one set of hydraulic parameters for the whole profile at each of the seven locations. The results of the verification experiment are shown in Fig. 3. In general, simulated T_a is within 10% of the reference T_a. However, simulated E_a and Q is seriously over and under predicted, compared to the corresponding reference values. At first instance, it could be speculated that it is not possible to define heterogeneous soil profile by a single set of effective parameters. This speculation is partly justified by the fact that, for the seven profiles, the top 10–20 cm layer is dominated by the sand fraction. The textural class varies for sub-surface layers representing medium to heavy soils (Fig. 1). The higher sand fraction in the surface layers results in less evaporation during forward simulations. However, when the profile is attempted to be defined by a single set of parameters, these will represent

Table 2
Different cases used during inverse identification of effective soil hydraulic parameters. E_a is simulated as minimum (min) of E_p and E_{max} or E_p, E_{max} and E_{emp} as the case may be. E_{emp} is as calculated with Boesten and Stroosnijder (1986) approach

Cases	Measurements	Number of soil layers during inversion	E_a simulation approach	Optimized parameters
1	ET	1	$\min(E_p, E_{max})$	α, n, θ_r, θ_s, k_s
2	ET	2	$\min(E_p, E_{max})$	α, n, θ_r, θ_s, k_s
3	ET	1	$\min(E_p, E_{max}, E_{emp})$	α, n, θ_r, θ_s, k_s
4	ET	1	$\min(E_p, E_{max}, E_{emp})$	Scale factor, θ_s
5	ET	1	$\min(E_p, E_{max}, E_{emp})$	α, θ_s, k_s
6	ET + θ	1	$\min(E_p, E_{max}, E_{emp})$	α, θ_s, k_s

the average conditions of the whole profile (including top 10–20 cm). Soil evaporation is mostly determined by the soil moisture content and hydraulic conductivity in the surface layer. This means that there is always a possibility of over estimation of the E_a. To overcome this problem, Case 2 was designed.

In Case 2, an attempt is made to identify two sets of parameters, one for the top 15 cm soil profile and the other for the rest of the profile (15–120 cm). The results of the verification experiment are also shown in Fig. 3. Though there is some improvement in the simulated E_a and Q for some of the soil profiles, the results are far from satisfactory. Common to both the cases is that the simulated T_a is predicted reliably while E_a is over-predicted grossly. This means that even when the given soil profile is identified with two sets of parameters, the resulting parameters for the top layer are not representative. In fact, the problem arises due to the dependence of E_a on the soil hydraulic functions of the top layers when it is simulated based on Darcy's flux. Therefore, we designed Case 3 as same to Case 1 but now E_a is simulated according to minimum of E_p, E_{max} or E_{emp}. Accordingly we also repeated the forward simulations to generate appropriate reference set of the water balance components for the changed option for E_a. Under actual field conditions also, the applicability of Darcy flux approach for E_a is questionable (van Dam, 2000). Therefore, the shift in E_a option is a practical assumption as well.

Except for the option of E_a simulation Case 1 and Case 3 are similar. The results of the verification experiments are shown in Fig. 4. There is a considerable improvement in the performance of inversely identified soil hydraulic parameters as compared to Case 1 and Case 2 (Fig. 3). However, some over predictions of the simulated E_a are to be noted. This suggests that the identified parameters for top layer are still being influenced by the whole profile behaviour through ET_a as used in the inverse problem. This is due to the fact that E_a is still affected by the soil hydraulic parameters whenever E_{max} governs the evaporation process.

In many applications, basic information of the soil texture or soil hydraulic functions is available. Although the sensitivity of VG parameter n to the ET_a is relatively higher than that to the parameters α

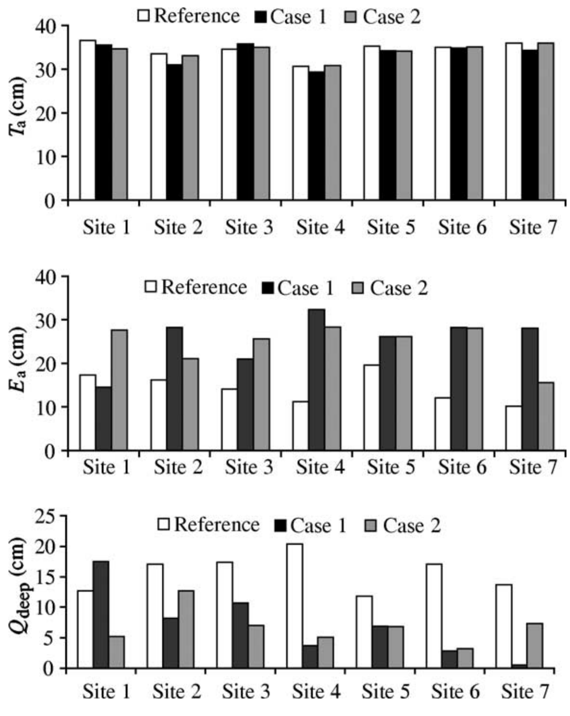

Fig. 3. Hydrological behaviour of inversely identified soil hydraulic parameters for Case1 and Case 2.

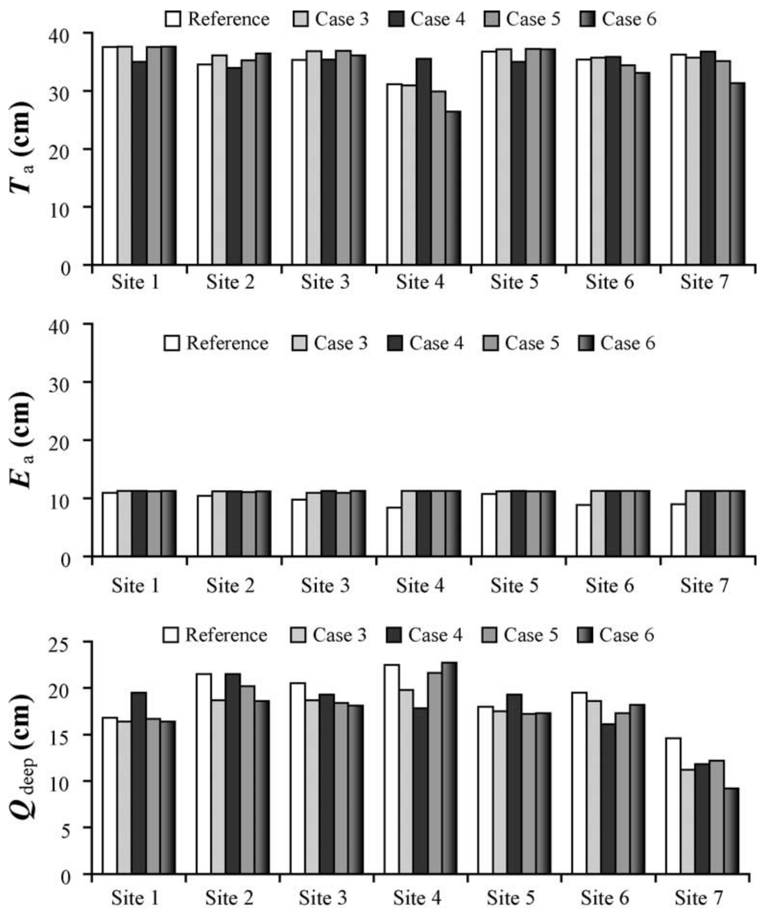

Fig. 4. Same as Fig. 3 but for different cases.

(Jhorar et al., 2002), the parameter n is more directly related to soil textural class and a good estimate can be arrived at based on available information. In such cases, optimization of scale factor ρ_{scal} and θ_s is probably sufficient to derive suitable soil hydraulic functions (van Dam, 2000). According to the scaling theory, α and k_s at any location are related to ρ_{scal} and their corresponding reference values ($\alpha = \rho_{scal}\alpha_{ref}$; $k_s = \rho_{scal}^2 k_{s,ref}$). Replacing α_{ref}; and $k_{s,ref}$ by their initial guess α_{guess}; and $k_{s,guess}$, it is possible to optimize both α and k_s by optimizing only ρ_{scal}. Accordingly, in Case 4, scale factor ρ_{scal} and θ_s, are optimized. For this Case, we fixed n ($= 1.6$) and θ_r ($= 0.05$) during optimization. In practice, these values can be selected based on available information on soil textural class. The results (Fig. 4) are not consistently better than Case 3. This may be due to fixing of n at one value for all the soil profiles. On the other hand site 4 and 7 have relatively larger clay content in sub-surface layers (Fig. 1) and a smaller value of n for these sites would have been more appropriate (Carsel and Parrish, 1988; also see Table 2). Another reason could be that the scale factor can only modify α and k_s in one direction ($\alpha = \rho_{scal}\alpha_{guess}$; $k_s = \rho_{scal}^2 k_{s,guess}$). Therefore, a suitable guess of reference α and k_s is very important. Since the ultimate goal is to derive area effective soil hydraulic parameters, these issues are discussed in Section 3.2.

To overcome the limitation of scale factor, Case 5 was designed, wherein both α and k_s along with θ_s are optimized. All the three parameters (α, k_s and θ_s) were determined with much smaller confidence interval than for the Case 3. As can be seen from the results of the verification experiment (Fig. 4), Case 5 performs slightly better than Case 3 and Case 4. This further justifies the speculation regarding the limitation of the scale factor as the favourable effect of less number of optimized parameters was not observed when scale factor was optimised. Therefore, it may be concluded that, if textural information is available, it is better to optimize only α, k_s and θ_s rather than optimizing the scale factor or all the VG model parameters. The validity of this conclusion will be further checked while deriving area effective soil hydraulic parameters. The inability of Case 5, to simulate more closer hydrological behaviour for site 7 may be attributed to the fixing of n at a relatively higher value for this site.

Information on different relevant observations which are sensitive to the system parameters being optimized is a desirable feature for the inverse problems. We designed Case 6 considering the potential of satellite remote sensing to provide information on the root zone soil moisture together with ET_a fluxes. In fact it is the only case where we use $ET - \theta$ based form of the objective function (Eq. (4)). Addition of θ_{rz} in the objective function slightly improved the simulated root zone soil moisture. However, there is no considerable improvement in the hydrological behaviour (Fig. 4) of the inversely identified soil hydraulic parameters. This means that use of ET-based objective function is as good as $ET - \theta$ based form of the objective function for the soil profiles considered and for the imposed initial and boundary conditions. Accordingly, only ET-based form of the objective function (Eq. (4)) will be used to inversely define area effective soil profile in this paper.

3.2. Area effective soil profile

3.2.1. Areal fluxes

A further analysis of the data on soil profile texture (45 samples) of the Kheri distributary area as reported by Sood (1969) showed that the seven sites, respectively, represents 0.31, 0.20, 0.04, 0.02, 0.37, 0.04 and 0.02 fraction of the area. Therefore, the above fractions are assigned as the values of F_i in Eq. (3) to estimate areal evapotranspiration ET_a^* representing the whole command area of the distributary. In this study, we consider one-dimensional vertical flow. This means that lateral flow between sub-areas is ignored. One-dimensional flow is a practical assumption for deep groundwater level conditions because the deep lateral groundwater movement does not affect the near surface soil moisture conditions. For flows from wetting at soil surface (irrigation), the vertical gradients would be sufficiently larger than any horizontal gradient so that flow between the sub-areas may be neglected. A similar approach to that of ET_a^* was followed to derive reference set of other water balance components for whole command area. Thereafter, ET_a^* observation for the 12 days is used as input to the objective function to derive area effective soil hydraulic parameters.

3.2.2. Area effective soil hydraulic parameters

Based on the results of individual soil profiles, Case 3, 4 and 5, of Table 2 are used to inversely identify area effective soil hydraulic parameters. In order to examine the uniqueness of the results, the optimization process was repeated with different initial guess of the parameters (α, k_s and θ_s). Again, the performance of the inversely identified area effective parameters was tested through numerical verification experiments. The verification experiment described in the previous sections (hereinafter referred to as wet verification experiment) represent relatively heavier depths of irrigation application. Such irrigation depths are common in the study area due to the use of flood irrigation method on light textured soils. However, another verification experiment (hereinafter referred to as dry verification experiment) was also carried out, for relatively shallow depths of irrigation application. In this case a total of 250 mm irrigation against 700 mm in the wet verification experiment was specified. For many applications, it may be sufficient to know only accurate information on seasonal water balance components. However, for some specific application, it may be important to have reliable information on temporal variation of different water balance components as well. Therefore, the performance of inversely identified parameters was examined with respect to seasonal as well as temporal hydrological behaviour.

3.3. Seasonal water balance components

Table 3 shows the mean and coefficient of variation CV of seasonal simulated water balance components

Table 3
Reference and mean value of simulated areal seasonal simulated water balance components (mm) for wet verification experiment for Case 3, Case 4 and Case 5. The results of simulations are based on five different initial guess of fitting parameters

Water balance component	Reference	Case 3		Case 4		Case 5	
		Mean	CV	Mean	CV	Mean	CV
E_a	106	112	0.000	113	0.000	113	0.004
T_a	363	365	0.009	356	0.049	361	0.034
ET_a	469	477	0.007	469	0.037	474	0.026
Q	185	186	0.022	187	0.103	180	0.071
ΔS	46	38	0.029	45	0.052	46	0.024

for wet verification experiment. The mean value of different water balance components as simulated by different Cases is quite close for the wet verification experiment. The CV values are smallest for Case 3 followed by Case 4 and Case 5. In fact for one of the initial guess, the Case 4 resulted in over prediction of Q by more than 15% which is reflected in higher value of CV (0.103). On the other hand, Case 3 and 5, predicted all the water balance components within 10% of the reference set. This means that, reducing the number of parameters by optimizing scale factor does not produce favourable effects in our case. The smaller CV values of different water balance components demonstrate the uniqueness of model predictions with inversely identified parameters.

The CV values of simulated seasonal water balance components for the dry verification experiment are given in Table 4. Again, the CV values are smallest for Case 3 followed by Case 4 and Case 5. Simulated and reference Q and ΔS is negligible for this verification experiment. The reference and simulated ET_a is quite similar, but E_a is over predicted and T_a is under predicted by different fitted parameters. The deviation between reference and simulated E_a and T_a is minimum for Case 3 followed by Case 4 and Case 5. Even the Case 3 over predicts E_a by 30% and under predicts T_a by 7%. Due to relatively smaller proportion of E_a (28%) into ET_a, the over prediction has little effect on the total ET_a. A comparison of the mean and CV values of ET_a with that of E_a and T_a indicate that prediction of ET_a is much more accurate and reliable than that of separate prediction of E_a and T_a.

3.4. Temporal water balance components

In order to examine the reliability of inversely identified parameter for temporal hydrological behaviour, the root mean square error (RMSE) of the daily values of different water balance components were computed. The resulting RMSE values together with mean values of simulated and reference water balance components are given in Table 5. The RMSE values are based on the entire simulation period of 160 days. The RMSE values follow more or less the similar trend as that of CV of cumulative water balance components except for Q. The RMSE values of the simulated daily ET_a are within 20% of the mean value

Table 4
Same as Table 2 but for dry verification experiment

Water balance component	Reference	Case 3		Case 4		Case5	
		Mean	CV	Mean	CV	Mean	CV
E_a	70	92	0.010	100	0.096	99	0.094
T_a	180	167	0.008	152	0.098	154	0.088
ET_a	250	258	0.002	252	0.021	253	0.017
Q	2	1	0.056	1	0.468	1	0.340
ΔS	2	1	0.000	3	1.013	4	1.009

Table 5
Root mean square error (RMSE) (mm d^{-1}) and mean (mm d^{-1}) value of area daily simulated water balance components for Case 3, Case 4 and Case 5. The results are based on simulation period of 160 days for a typical optimization

Water balance component	Reference	Case 3		Case 4		Case 5	
		Mean	RMSE	Mean	RMSE	Mean	RMSE
Wet verification experiment							
E_a	0.66	0.70	0.066	0.70	0.080	0.70	0.080
T_a	2.27	2.25	0.096	2.07	0.374	2.20	0.117
ET_a	2.93	2.95	0.095	2.77	0.317	2.91	0.091
Q	1.16	1.20	3.153	1.35	1.980	1.18	0.955
Dry verification experiment							
E_a	0.44	0.58	0.207	0.69	0.313	0.66	0.283
T_a	1.13	1.03	0.133	0.85	0.486	0.90	0.348
ET_a	1.57	1.61	0.180	1.54	0.359	1.56	0.258
Q	0.01	0.00	0.011	0.01	0.013	0.01	0.010

except for Case 4 for dry verification experiment. Surprisingly, the Case 3 has a very high RMSE value (3.2 mm d^{-1}) for simulated Q. This suggests that if all the VG model parameters are optimized based on ET fluxes, the resulting parameters may not reproduce reliable estimate of temporal Q. Reliable prediction of temporal Q may be quite important for certain application, e.g. to determine peak drainage coefficient for the design of regional drains.

To further examine the performance of different Cases in reproducing the temporal variation of Q, the simulated and reference daily Q is also shown in Fig. 5. The high RMSE value of simulated Q (Table 5) is due to the over prediction of Q during the period immediately following irrigation, particularly for relatively larger depth of irrigation (20 cm) on day 1. Though there are some over predictions of Q by Case 5, during periods immediately following different irrigation events, the overall performance of Case 5 in comparison to Case 3 and 4 is noteworthy. This further justifies the earlier conclusion that, if VG model parameters are optimized based on ET fluxes, it is more appropriate to optimize α, k_s and θ_s rather than optimizing scale factor or all the VG model parameters. This also means that some information on the textural soil class of the area under consideration, to assign appropriate value for parameter n and θ_r, is an important input to define area effective soil hydraulic parameters using ET fluxes.

3.5. Soil water retention curve

Fig. 6 shows the area effective soil water retention curve as derived from inverse modelling approach for

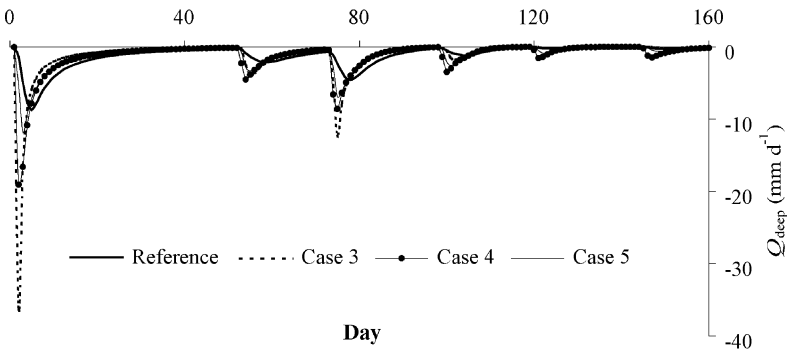

Fig. 5. Temporal variation of area effective reference and simulated Q, at 120 cm depth, for the wet verification experiment using inversely identified soil hydraulic parameters.

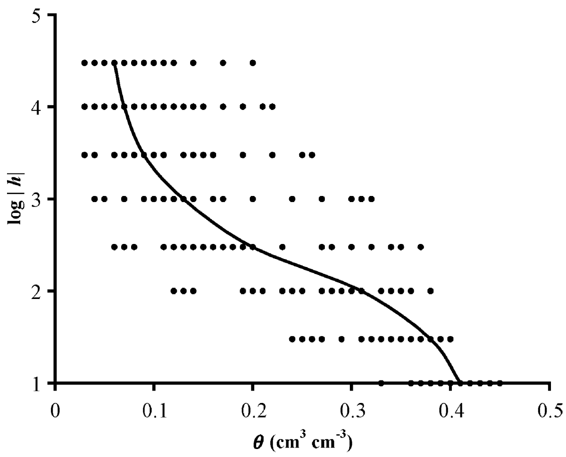

Fig. 6. Soil water retention characteristics of different layers of seven profiles used in the study. Also shown is the area effective soil water retention curve as derived from inverse modelling approach (Case 5). h is in the units of cm.

the best performing case (Case 5). Also shown are the soil water retention characteristics of different layers encountered in the study area. It is important to note that despite a large variation in the soil water retention characteristics of different soil layers, the identified area effective curve reproduced water balance components quite reasonably well.

4. General discussion

The results of the present study are based on soil profiles having a relatively high sand fraction in surface layers. The soil evaporation process is mainly governed by the surface layers. Therefore, any alteration of soil hydraulic parameters for the top layer is expected to affect simulated E_a. When the heterogeneous soil profiles are defined by single homogeneous soil profile, the whole profile effective soil hydraulic parameters are also assigned to the surface layers. In our case, sub-surface soil layers varied greatly in texture. This results in over prediction of E_a by the inversely identified soil hydraulic parameters. Other conditions may arise in the field situation when surface layers are of relatively heavier texture than sub-surface layers. Under such situations, it may be expected that the effective soil hydraulic parameters derived by the present approach may result in under prediction of the soil evaporation. Therefore, if the surface soil layers have deviating soil hydraulic properties and if T_a and E_a are to be simulated separately and interpreted independently, care must be taken not to give undue attention to absolute values while comparing different scenarios. Alternatively, it may be more appropriate to identify the soil hydraulic parameters of the surface layer independently or an alternative approach must be adopted to simulate E_a. Further, the wide differences in the inverse results when using different approaches of E_a simulation indicate that the simulation of E_a should be given serious attention while attempting to inversely identify soil hydraulic functions for heterogeneous soil conditions. One approach to tackle this problem could be to derive the parameters for the top layer using remotely sensed soil evaporation under bare field conditions as input to the objective function.

The acceptable performance of inversely identified soil hydraulic parameters in predicting the total ET and Q is encouraging. For irrigated agriculture in arid and semi-arid regions, assessment of water logging risks (directly related to total Q) is a critical issue. The inversely identified soil hydraulic parameter are sufficient to make simple water balance computation to evaluate the performance of irrigation systems under such regions.

In this study, we have considered only the mixture of soils while deriving area effective soil profiles. However, in reality there could also be a mixture of different crops at the scale of model application. It is beyond the scope of this paper to deal with this problem, as our aim was to know if a mixture of heterogeneous soil profiles can be defined by an overall effective soil profile. However, we do suggest a simple framework to account for the crop heterogeneity. Referring to Fig. 2, instead of a single simulation run for a given set of parameters (as estimated by each PEST run), the simulation model (in this case SWAP) can be run for a number of crops in the area. The simulated ET fluxes for different crops can than be averaged before supplying them as output to the objective function.

5. Conclusions

Various problems associated with the assignment of effective soil hydraulic parameters for heterogeneous soil profiles has been addressed. An attempt has been made to derive effective soil hydraulic parameters for a typical area consisting of spatially variable heterogeneous soil profiles. It has been highlighted that the process of deriving effective soil hydraulic parameters for heterogeneous soil profiles is not as straight forwards as for homogeneous soil profiles.

In this study the actual soil evaporation could not be predicted accurately by the inversely identified soil hydraulic parameters due to deviating soil hydraulic properties of surface layers. If actual soil evaporation and transpiration are to be simulated separately and interpreted independently, simulation of soil evaporation should be given serious attention while deriving effective soil hydraulic parameters for field conditions having deviating hydraulic properties of surface layers.

The acceptable performance of inversely identified soil hydraulic parameters in predicting total evapotranspiration and deep percolation is encouraging. It has been shown that, it is possible to define an area having spatially variable heterogeneous soil profiles by an equivalent single homogeneous soil profile, at least to make reliable water balance computations. The cumulative water balance components could be simulated accurately even when all the VG model parameters were optimized. However, to reproduce the temporally acceptable prediction of deep percolation loss, it is necessary that general information on textural layering is available for the area.

Results as obtained with forward and backward simulations carried out in the present study suggests that if selected modelling concept is an appropriate representation of the real system, evapotranspiration fluxes, along with general information on textural layering, are sufficient to derive area effective soil hydraulic parameters. Despite a large variation in the hypothetically constructed area, it was possible to reproduce good estimate of different water balance components. It means that even the satellite images with poor spatial resolution could be used to identify soil hydraulic parameters at the pixel level. Heterogeneity of different soil types within the pixel size is not a limitation.

References

Agarwal, M.C., Roest, C.W.J. (Eds.), 1996. Towards improved water management in Haryana state; final report of the Indo-Dutch operational research project on hydrological studies, Chaudhary Charan Singh Haryana Agricultural University, Hisar, Int. Inst. for Land Reclamation and Improvement/DLO Winand Staring Centre for Integrated Land, Soil and Water Res., Wageningen.

Ahuja, L.R., Naney, J.W., Nielsen, D.R., 1984. Scaling soil water properties and infiltration modeling. Soil Sci. Soc. Am. J. 48, 970–973.

Bastiaanssen, W.G.M., Singh, R., Kumar, S., Schakel, J.K., Jhorar, R.K., 1996. Analysis and recommendations for integrated on-farm water management in Haryana, India: a model approach. Report 118, SC-DLO, Wageningen, The Netherlands.

Batjes, N.H., 1996. Development of a world data set of soil water retention properties using pedotransfer rules. Geoderma 71, 31–52.

Black, T.A., Gardner, W.R., Thurtell, W., 1969. The prediction of evaporation, drainage, and soil water storage for a bare soil. Soil Sci. Soc. Am. J. 33, 655–660.

Boesten, J.J.T.I., Stroosnijder, L., 1986. Simple model for daily evaporation from fallow tilled soil under spring conditions in a temperate climate tilled soil under spring conditions in a temperate climate. Neth. J. Agric. Sci. 34, 75–90.

Braun, H.M.H., Kruijne, R., 1994. In: Ritzema, H.P., (Ed.), Drainage Principles and Applications, ILRI Publication 16, International Institute for Land Reclamation and Improvement, Wageningen, The Netherlands, pp. 77–110.

Burke, E.J., Gurney, R.J., Simmonds, L.P., O'Neill, P.E., 1998. Using a modeling approach to predict soil hydraulic properties from passive microwave measurements. IEEE Trans. Geosci. Remote Sens. 36, 454–462.

Carsel, R.F., Parrish, R.S., 1988. Developing joint probability distributions of soil water characteristics. Water Resour. Res. 24, 755–769.

Clausnitzer, V., Hopmans, J.W., Nielsen, D.R., 1992. Simultaneous scaling of soil water retention and hydraulic conductivity curves. Water Resour. Res. 28, 19–31.

van Dam, J.C., 2000. Field-scale water flow and solute transport: SWAP model concepts, parameter estimation and case studies. PhD Thesis. Wageningen University, The Netherlands.

van Dam, J.C., Feddes, R.A., 1996. Modeling of water flow and solute transport for irrigation and drainage. In: Pereira, L.S., Feddes, R.A., Gilley, J.R., Lesaffre, B. (Eds.), Sustainability of Irrigated Agriculture, Kluwer Academic, The Netherlands, pp. 211–231.

van Dam, J.C., Huygen, J., Wesseling, J.G., Feddes, R.A., Kabat, P., van Walsum, P.E.V., Groenendijk, P., Diepen, C.A., 1997. Theory of SWAP version 2.0. Department of Water Resources, Report 71, Wageningen Agricultural University, Wageningen, The Netherlands.

Doherty, J., Brebber, Whyte, P., 1995. PEST. Model Independent Parameter Estimation, Australian Centre for Tropical Freshwater Research, James Cooke University, Townsville, Australia.

Droogers, P., Kite, G., 1999. Water productivity from integrated basin modelling. Irrig. Drainage Syst. 13, 275–290.

Droogers, P., Bastiaanssen, W.G.M., Beyazgul, M., Kayam, Y., Kite, G.W., Murray-Rust, H., 2000. Distributed agro-hydrological modeling of an irrigation system in western Turkey. Agric. Water Manage. 43, 183–202.

D'Urso, G., Menenti, M., Santini, A., 1999. Regional application of one-dimensional water flow models for irrigation management. Agric. Water Manage. 40, 291–302.

Feddes, R.A., Kowalik, P.J., Zarandy, H., 1978. Simulation of field water use and crop yield. Simulation Monographs, Pudoc, Wageningen.

Feddes, R.A., Menenti, M., Kabat, P., Bastiaanssen, W.G.M., 1993a. Is large-scale inverse modelling of unsaturated flow with areal evaporation and surface soil moisture as estimated from remote sensing feasible? J. Hydrol. 143, 125–152.

Feddes, R.A., de Rooij, G.H., van Dam, J.C., Kabat, P., Droogers, P., Stricker, J.N.M., 1993b. Estimation of regional effective soil hydraulic parameters by inverse modeling. In: Russo, D., Dagan, G. (Eds.), Water Flow and Solute Transport in Soils, Advanced Series in Agricult. Sciences, vol. 20. Springer, Berlin, pp. 211–233.

Feyen, J., Jacques, D., Timmerman, A., Vanderborgt, J., 1998. Modelling water flow and solute transport in heterogeneous soils: a review of recent approaches. J. Agric. Engng Res. 70, 231–256.

van Genuchten, M.T., 1980. A closed form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Sci. Soc. Am. J. 44, 892–898.

Hollenbeck, K.J., Jensen, K.H., 1998. Experimental evidence of randomness and nonuniqueness in unsaturated outflow experiments designed for hydraulic parameter estimation. Water Resour. Res. 34, 595–602.

Hopmans, J.H., Simunek, J., 1999. Review of inverse estimation of soil hydraulic properties. In: van Genuchten, M.Th., Leij, F.J., Wu, L. (Eds.), Characterization and Measurement of the Hydraulic Properties of Unsaturated Porous Media, University of California, Riverside, CA, pp. 643–659.

Jensen, K.H., Mantoglou, A., 1992. Application of stochastic unsaturated flow theory, numerical simulations and comparisons to field observations. Water Resour. Res. 28, 269–284.

Jhorar, R.K., Bastiaanssen, W.G.M., Feddes, R.A., van Dam, J.C., 2002. Inversely estimating soil hydraulic functions using evapotranspiration fluxes. J. Hydrol. 258, 198–213.

Kabat, P., Hutjes, R.W.A., Feddes, R.A., 1997. The scaling characteristics of soil parameters: from plot scale heterogeneity to subgrid parameterization. J. Hydrol. 190, 363–396.

Kim, C.P., Stricker, J.N.M., Feddes, R.A., 1997. Impact of soil heterogeneity on the water budget of unsaturated zone. Water Resour. Res. 33, 991–999.

Li, W., Li, B., Shi, Y., Jacques, D., Feyen, J., 2001. Effect of spatial variation of textural layers on regional field water balance. Water Resour. Res. 37, 1209–1219.

Mantoglou, A., Gelhar, L.W., 1987a. Stochastic modelling of large scale transient unsaturated flow systems. Water Resour. Res. 23, 37–46.

Mantoglou, A., Gelhar, L.W., 1987b. Capillary tension head variance, mean soil moisture content. And effective specific soil moisture capacity in transient unsaturated flow in stratified soils. Water Resour. Res. 23, 47–56.

Mantoglou, A., Gelhar, L.W., 1987c. Effective hydraulic conductivities of transient unsaturated flow in stratified soils. Water Resour. Res. 23, 57–67.

Molden, D., Sakthivadivel, R., Perry, C.J., de Fraiture, C., Kloezen, W.H., 1998. Indicators for comparing performance of irrigated agriculture, Research Report 20, International Water Management Institute, Colombo, Sri Lanka.

Raats, P.A.C., 1990. Characteristic lengths and times associated with processes in the rootzone. In: Hillel, D., Elrick, D.E. (Eds.), Scaling in Soil Physics, Principles and Applications, SSA Special Publication No. 25, SSSA, Madison, pp. 59–72.

Reynolds, C.A., Jackson, T.J., Rawls, W.J., 2000. Estimating soil water holding capacities by linking the Food and Agriculture Organization soil map of the world with global pedon database and continuous pedotransfer functions. Water Resour. Res. 36, 3653–3662.

Saxton, K.E., Rawl, W.J., Romberger, J.S., Papendrick, R.I., 1986. Estimating generalized soil–water characteristics from texture. Soil Sci. Soc. Am. J. 50, 1031–1036.

Schaap, M.G., Leij, F.J., 2000. Improved prediction of unsaturated hydraulic conductivity with Mualem–van Genuchten model. Soil Sci. Soc. Am. J. 64, 843–851.

Schmugge, T.J., Jackson, T.J., Kustas, W.P., Wang, J.R., 1992. Passive microwave remote sensing of soil moisture: results from HAPEX, FIFE and MONSOON'90 ISPRS. J. Photogram. Remote Sens. 47, 127–143.

Smith, R.E., Diekkrüger, B., 1996. Effective soil water characteristics and ensemble soil water profile in heterogeneous soils. Water Resour. Res. 32, 1993–2002.

Snow, V.O., Bond, W.J., 1998. Inverse method to estimate mineralisation rate constants for nitrogen simulation models: interaction between sampling strategy and quality of parameter estimates. Aust. J. Soil Res. 36, 1–15.

Sood, S.K., 1969. A study of moisture retention characteristics of some soils irrigated by Bhakra canal. MSc Thesis. Punjab Agricultural University, Hisar, India.

Wagner, B.J., Gorelick, S.M., 1986. A statistical methodology for estimating transport parameters: theory and application to one-dimensional advective–dispersive systems. Water Resour. Res. 22, 1303–1315.

Wildenschild, D., Jensen, K.H., 1999. Numerical modelling of observed effective flow behaviour in unsaturated heterogeneous sands. Water Resour. Res. 35, 29–42.

Wösten, J.H.M., van Genuchten, M.Th., 1988. Using texture and other soil properties to predict the unsaturated soil hydraulic conductivity. Soil Sci. Soc. Am. J. 52, 1762–1770.