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ORIGINAL ARTICLE

WaSim model for subsurface drainage design using soil hydraulic parameters estimated by pedotransfer functions

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Abstract

The agricultural drainage engineering community is steadily shifting the design of subsurface drainage systems from the experience-based design approach to the simulation-based design approach. As with any design problem, two challenges are faced; firstly, how to determine all the input data required by the simulation model, and secondly to, a priori, anticipate what the performance of the designed system will be. This study sought to evaluate the performance of the WaSim model to simulate fluctuating water table depths (WTD), and drainage discharges (DD) in KwaZulu-Natal Province, South Africa. Saturated hydraulic conductivity (K_{sat}), which is an input to the WaSim model, was estimated by the Rosetta computer program, based on soil particle size distribution data, bulk density, and soil water retention characteristics at pressure heads of −33 and −1500 kPa. performance of the WaSim model was statistically assessed using the coefficient of determination (R^2), coefficient of residual mass (CRM), mean absolute error (MAE), mean percent error (MPE), and the nash–sutcliffe efficiency (NSE). during the validation period, the WaSim model predicted WTDs with R^2, CRM, MAE, MPE, and NSE of 0.86, 0.003, 4.9 cm, 6.0%, and 0.98, respectively. In the same validation period, the model predicted DDs with R^2, CRM, MAE, MPE, and NSE of 0.57, 0.002, 0.30 mm day^{-1},11%, and 0.76, respectively. These results suggest that the use of Rosetta-estimated K_{sat} data as inputs to the WaSim model compromised its accuracy and applicability as a subsurface drainage design tool. Owing to the relatively low R^2 value of 0.57, and that the WaSim model was empirically developed, we recommend further improvement on the calibration of the model for it to be suitable for application under the prevailing conditions. Also, in the absence of other means of determining K_{sat}, we caution the use of Rosetta-estimated K_{sat} data as inputs to the WaSim model for the design and analysis of subsurface drainage systems in KwaZulu-Natal Province, South Africa.

Keywords Drainage · Pedotransfer functions · Rosetta · WaSim · Water management

Introduction

The provision of artificial agricultural subsurface drainage continues to be a key element in enhancing crop production potential of irrigated lands. The design of agricultural subsurface drainage systems has been a subject of discussion lately, and consequently, it has seen a number of improvements. According to ASAE (1999), the design of subsurface drainage systems is largely dependent on the experience in handling similar problems, also known as Experience-Based Design Approach (EBDA). This approach is, however, unreliable as it results in either an over- or under-designed subsurface drainage system. The development of drainage simulation models in the past five decades is steadily shifting the agricultural drainage engineering community from designing subsurface drainage systems based on the EBDA approach to a Simulation-Based Design Approach (SBDA) (ASAE 1999). One major advantage of the SBDA over the EBDA is the flexibility it provides to conduct analyses of the performance of subsurface drainage systems at various combinations of design parameters, as well as providing an idea of the system's performance prior to installation. DRAINMOD model (Skaggs 1978), Water Simulation (WaSim)

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model (Hess et al. 2000), and SaltMOD model (Oosterbaan 2000) are some of the model examples which have been used as subsurface drainage design decision support tools in Australia (Yang 2008), India (Hirekhan et al. 2007), and Turkey (Bahceci et al. 2006). Unlike the EBDA, the application of these simulation models clearly shows that the SBDA is a simpler and cost-effective means of designing subsurface drainage systems.

Despite the promising progress and the steady growth in the development of drainage simulation models, Bastiaanssen et al. (2007) argue that the adoption of drainage simulation models, as agricultural water management decision support tools, still remains a challenge in most regions. Madramootoo et al. (2009), Salazar et al. (2008), Manyame et al. (2007), Bahceci et al. (2006), and Borin et al. (20000, attribute this scenario to (i) the unavailability of good quality soil hydraulic conductivity (K_{sat}) and Soil Water Retention Characteristics (SWRC) data, which are critical input parameters to many drainage simulation models, and (ii) the unavailability of user-friendly computer based drainage simulation models suitable for both the low and middle level agricultural water managers. A good example is the DRAINMOD model, which despite successful calibration and validation results in the sugarcane fields of KwaZulu-Natal, South Africa (Malota and Senzanje 2015), still faces adoption challenges. van der Merwe (2003) reports the lack of a drainage simulation model with an easy-to-follow graphical user interface and the unavailability of reliable K_{sat} and SWRC data as the two main determining factors to the adoption of a simulation based drainage design approach in the area.

Accurate field estimation of K_{sat} and SWRC require precise equipment, which is expensive and not readily available in most regions (Liu et al. 2017). On the other hand, laboratory estimation of these soil hydraulic parameters is time consuming and often over-estimate the parameters (Moriasi et al. 2007), thus rendering them unreliable for purposes of modeling soil hydraulic processes (Zhang et al. 2017). Researchers have however shown a keen interest in developing a number of indirect methods to estimate soil hydraulic parameters from easily measured and obtainable data (e.g., Rawls and Brakensiek 1985; Rawls et al. 1991; van Genuchten and Liej 1992; Pachepsky et al. 1996). Bouma and van Lanen (1987) regard such indirect methods as Pedotransfer Functions (PTFs), due to their ability to translate basic and easily accessible soil data and information to soil hydraulic parameters.

Rosetta (Schaap et al. 2001), with its neural network-based PTFs, is one of the successful computer programs that has been extensively used in soil hydraulic data scarce regions to estimate K_{sat} values and SWRCs (e.g., Salazar et al. 2008). Rosetta estimates these soil hydraulic parameters based on soil bulk density, soil particle size distribution (% sand, clay and silt), and one or two known points on the Soil Water Retention Characteristic Curve (SWRCC) (e.g., Zhang et al. 2017; Salazar et al. 2008; Wosten et al. 2001; Manyame et al. 2007). On the other hand, WaSim model (Hess et al. 2000), a subsurface drainage model with a graphical user interface and a relatively small data input requirement (Hirekhan et al. 2007), as opposed to the DRAINMOD model, offers an excellent opportunity to enhance drainage model adoption in regions such as KwaZulu-Natal, South Africa, where problems of poor agricultural drainage require urgent attention (van der Merwe 2003). The objective of this study was to assess the performance of the WaSim model to simulate the fluctuation of mid-drain spacing water table depth and drainage discharges using soil hydraulic input parameters estimated by the Rosetta computer program. The study was conducted in a sugarcane field in KwaZulu-Natal Province, South Africa.

Materials and methods

Description of the WaSim model

The WaSim model was developed by Cranfield University and HR Wallingford to simulate changes in soil water content and water table depths as a function of soil hydraulic properties, weather, and water management systems. The model, according to Hess et al. (2000), uses a three soil layer water balance existing between the upper (soil surface) and the lower boundaries (impermeable layer) as depicted in Fig. 1. Recharge to the soil system could either be in the form of rainfall, irrigation or seepage, with evaporation and

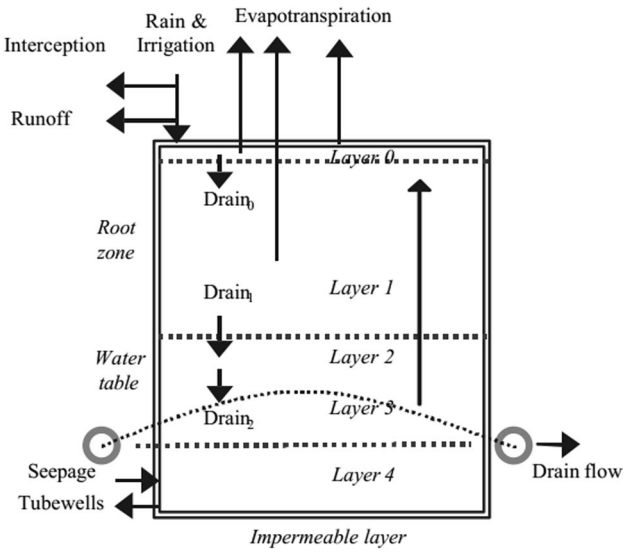

Fig. 1 An overview of the multi soil layer water balance in the WaSim Model (after Hess et al. 2000)

deep percolation treated as outputs from each soil layer. In each case, deep percolation and capillary rise from one soil layer further constitute an input component into the underlying and overlying soil layers, respectively.

The WaSim model adopts Eq. 1 (Youngs et al. 1989) to estimate drainage discharge on a daily basis.

$$q = 1000\frac{K_{sat}}{(L/2)^{\beta}}\left[(\varphi/2)^{\beta} - h^{\beta}\right] \quad (1)$$

where q is the daily drainage discharge (mm day^{-1}), L is the drain spacing (m), K_{sat} is the overall saturated hydraulic conductivity (m day^{-1}), soil water fraction

φ is the inside diameter of the drain pipe (m), h is the mid-drain spacing water table depth (m), and β is an exponent (dimensionless), which is dependent on drain spacing (L) and depth to the impermeable layer (d_0) (m), and is estimated as;

$$\beta = 2\left[d_0/(L/2)\right]^{d_0/(L/2)} \quad \text{for} \quad \frac{d_0}{(L/2)} < 0.35 \quad (2)$$

Otherwise,

$$\beta = 1.36$$

Mid-drain spacing water table depths are estimated using Eq. 3, which requires volume water fractions at field capacity and saturation points to estimate the drainable porosity and the total daily net flux from the groundwater table.

$$h_i = h_{i-1} - \frac{q + V_S}{1000\mu} \quad (3)$$

where μ is the drainable porosity (dimensionless) and is given as:

$$\mu = \frac{\int_0^{h_2}\theta_2(h)\mathrm{d}h - \int_0^{h_1}\theta_1(h)\mathrm{d}h}{h_2 - h_1} \quad (4)$$

where h_i is the water table depth (m) at any time ($t = t_1$), h_2 is the water table depth at any time ($t = t_2$), V_S is the total daily net flux (capillary rise) from the groundwater table to the root-zone (mm day^{-1}), $\theta_1(h)$ and $\theta_2(h)$ are soil water fractions (cm^3 cm^{-3}) as a function of soil depth (h) for water table positions at t_1 and t_2, respectively. The reader is referred to Hess et al. (2000), where a detailed theoretical description of the WaSim model is given.

Description of the rosetta

Rosetta (Schaap et al. 2001) is a computer program, which according to Salazar et al. (2008) implements five hierarchical PTFs to estimate soil SWRC, and saturated and unsaturated hydraulic conductivities. The program estimates the K_{sat} values based on surrogate data such as particle size distribution, bulk density and/or SWRC at one or two known points on the SWRCC (i.e., soil moisture content at – 33 and – 1500 kPa). The computer program estimates the soil parameters using the van Genuchten water retention model (Eq. 5) (Schaap et al. 2001)

$$\theta(h) = \theta_r + \frac{\theta_s - \theta_r}{[1 + (\alpha h)^n]^{1-(1/n)}} \quad (5)$$

where θ is the soil water fraction (cm^3 cm^{-3}) at a given suction (h) (cm, taken positive for increasing suctions), θ_s and θ_r are saturated and residual soil water fractions (cm^3 cm^{-3}), respectively, n (> 1) is the measure of pore-size distribution, and α (> 0) is related to the inverse of air entry pressure (cm^{-1}) (van Genuchten 1980).

Using Eq. 5, in connection with the Mualem (1976) pore-size distribution model (Eq. 6), yields the van Genuchten–Mualem model (Eq. 7), which according to van Genuchten (1980) and Schaap et al. (2001), is then used to estimate K_{sat} values.

$$K_r(S_e) = \frac{S_e^L\left\{\int_0^{S_e}\left[1/h(S_e)\right]\mathrm{d}S_e\right\}^2}{\left\{\int_0^1\left[1/h(S_e)\right]\mathrm{d}S_e\right\}^2} \quad (6)$$

$$K_r(S_e) = K_0 S_e^L\left\{1 - \left[1 - S_e^{n/(n-1)}\right]^{1-(1/n)}\right\}^2 \quad (7)$$

where S_e is the effective saturation (cm^3 cm^{-3}) (Vereecken et al. 2010; Jong van Lier and Pinheiro 2018) and is given as:

$$S_e = \frac{\theta(h) - \theta_r}{\theta_s - \theta_r} = \left[1 + (\alpha h)^n\right]^{n/(1-n)} \quad (8)$$

where K_r is the relative hydraulic conductivity, which is the ratio of hydraulic conductivity (K) at a certain soil water fraction (θ) and suction (h) to the hydraulic conductivity at saturation (K_{sat}), i.e., $K_r(\theta, h) = [K(\theta, h)]/K_{sat}$, K_0 is the matching point at saturation (m day^{-1}) and is comparable, but not entirely equal to K_{sat}, and L (< 0) is an empirical connectivity parameter, in most cases taken as 0.5 (Mualem 1976).

Study site

The study was conducted in an irrigated sugarcane field in Pongola, KwaZulu-Natal Province, South Africa. The total area of the sugarcane field is 32 ha. Pongola is located on the north-eastern side of South Africa, close to the South African and Swaziland border in the KwaZulu-Natal province

(27° 23′ 0″ South and 31° 37′ 0″ East). The area is dominated by clay-loam and clay soils (van der Merwe 2003) with fairly gentle slopes. The Aridity Index (*AI*) for the area is reported to be 0.12 (Malota and Senzanje 2015), which according to UNESCO (1979), is the ratio of mean annual rainfall (*P*) (mm) to mean annual reference potential evapotranspiration (ET_o) (mm). This Aridity Index characterizes the area to be an arid region ($0.03 < \mathrm{AI} < 0.20$). Thus, from April to October (winter season), crop production relies on irrigation only, while from November to March (summer season), some rainfall is available for crop production. The first subsurface drainage system was installed at the site in 1995 and was later replaced by a redesigned system in 2003 with a reduced drain spacing from 72 to 54 m, while the drain depth was maintained at 1.8 m.

Measurement of soil physical and hydraulic properties

Saturated soil hydraulic conductivity (K_{sat}) values were measured using an in situ method, i.e., the auger-hole method (van Beers 1983). Three 70 mm diameter auger-holes were drilled in each of the upper and middle sections, while four auger-holes were drilled in the lower section of the field. This made a total of 10 hand-drilled auger-holes in the whole 32 ha field, where in situ measurement of hydraulic conductivity were conducted. Determination of this number of testing locations was guided by Oosterbaan (1991), who recommends at least two sampling points per 10 ha. All the auger-holes were drilled to a depth of 1.7 m, well below the water table depth. The reader is referred to van Beers (1983) where a step by step auger-hole K_{sat} measurement procedure which was adopted in this study is presented. Prior to carrying out K_{sat} tests, five trenches were dug in the field (north, south, east, west and center) to a depth of 2.3 m from the soil surface. This was done to characterize any heterogeneities in soil layer boundaries and also to determine the number and thicknesses of the soil profile layers from the soil surface.

Saturated hydraulic conductivity values were also estimated using the Rosetta program, whose inputs were soil particle size distribution (% sand, silt and clay), soil bulk density (g cm^{-3}), and soil moisture contents at –33 kPa and –1500 kPa. The soil profile from the soil surface to the drain depth level had two soil layers, with the upper soil layer being 0.45 m, while the second layer was 1.55 m thick. Soil particle size distribution were determined using undisturbed soil samples, which were collected using cores from the second soil layer at each of the 10 locations, where auger-hole tests were conducted. The soil samples were collected at random points within the same second soil layer in which the water table was resting during auger-hole K_{sat} measurement (between 0.50 and 1.60 m from the soil surface). First to be determined were the soil bulk densities, which were later followed by particle size analysis, using the standard thermo-gravimetric and sieve-pipette methods (Gee and Bauder 1986). These measurements were done under laboratory conditions in the School of Engineering, University of KwaZulu-Natal. The reader is referred to Warrick (2002), where detailed descriptions of the two standard methods adopted in this study are presented.

Determination of soil water retention values (*h*) (*m*) and their corresponding soil moisture contents (θ) (cm^3 cm^{-3}) were done using a pressure plate in the hydraulic laboratory at the University of KwaZulu-Natal. Firstly, the soil samples were carefully submerged in water for 24 h in order to attain their saturated moisture content. This was later followed by placing the soil samples in the pressure chamber of the pressure plate and then subjecting them to pressures of 0 m, 20 m, 40 m, 60 m, 100 m, 120 m and160 m until no more water was observed to drain from the soil sample. This was followed by measuring the moisture content of the soil samples at each level of pressure head. The soil moisture content was measured using the thermo-gravimetric method which is again well described by Warrick (2002). The $\theta(h)$ data for each of the 10 soil samples were fitted to the van Genuchten soil water retention model in the RETC computer program (van Genuchten and Leij (1992), from which SWRCC were developed. RETC (RETention Curves) is a computer program which is capable of describing hydraulic properties of unsaturated soils (van Genuchten and Leij (1992). The program adopts a nonlinear squares approach to estimate unknown model parameters based on observed retention and hydraulic conductivity data. The reader is referred to Daniel and Wood (1971) and van Genuchten and Leij (1992) for a thorough description of PTFs which are implemented by the RETC program.

Values of soil moisture content at –33 and –1500 kPa for each of the soil samples (obtained from the SWRCC), as well as their particle size distribution and bulk density data were imputed in the Rosetta computer program to estimate K_{sat} values. The Rosetta estimated K_{sat} values were compared to the in situ measured K_{sat} values using five statistical indices, namely the Mean Absolute Error (MAE) (El-Sadek 2007), the Pearson's product-moment correlation (Coefficient of Determination) (R^2) (Wang et al. 2006), also known as the Goodness-of-fit (Shahin et al. 1993; Legates and Mc Cabe 1999; Vazquez et al. 2002), the Coefficient of Residual Mass (CRM) (El-Sadek 2007), the Mean Percent Error (MPE) (Moriasi et al. 2007), and the Nash–Sutcliffe Model Efficiency (NSE) (Moriasi et al. 2007).

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} (O_i - P_i)}{N} \tag{9}$$

$$R^2 = \left[\frac{\sum_{i=1}^{N} (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N} (O_i - \bar{O})^2 \sqrt{\sum_{i=1}^{N} (P_i - \bar{P})^2}} \right]^2 \quad (10)$$

$$\mathrm{CRM} = \frac{\sum_{i=1}^{N} O_i - \sum_{i=1}^{N} P_i}{\sum_{i=1}^{N}} \quad (11)$$

$$\mathrm{MPE} = \sum_{i=1}^{N} \left(\frac{|O_i - P_i|}{O_i} \right) 100\% \quad (12)$$

$$\mathrm{NSE} = 1 - \frac{\sum_{i=1}^{N} \left(O_i - P_i \right)^2}{\sum_{i=1}^{N} \left(O_i - \bar{O} \right)^2} \quad (13)$$

where P_i is the simulated value, O_i is the observed value, and N is the number of data entries.

MAE describes the accuracy of a model in making right predictions by measuring the average magnitude of errors between the simulated and the observed values (Legates and Mc Cabe 1999; Vazquez et al. 2002). According to Moriasi et al. (2007) and El-Sadek (2007), the MAE has a minimum value of 0.0, with values closer to 0.0 indicating a better agreement between measured and estimated values. The Goodness-of-fit measures how the estimated and measured data sets correlate and has minimum and maximum values of 0.0 and 1.0, respectively, with values closer to 1.0 indicating a better correlation between the two data sets (Shahin et al. 1993; Legates and Mc Cabe 1999; Vazquez et al. 2002). The CRM characterizes the tendency to over-estimate (CRM < 0) or under-estimate a property (CRM > 0) (El-Sadek 2007). The NSE measures the efficiency in predicting the values, with values closer to 1.0 indicating acceptable levels of efficiencies (Moriasi et al. 2007). On the other hand, MEP measures the magnitude of errors between the measured and predicted values relative to the measured values. MPE values closer to zero indicate that the predicted values are very close to the measured values (Legates and Mc Cabe 1999).

Measurement of water table depth and drainage discharges

Water table depths were measured at five piezometers which were manually augured at mid-drain spacing to a depth of 1.7 m from the soil surface. WTDs at each piezometer were measured by gradually lowering an electronic dip meter in the piezometer until a sound was heard. Under laboratory conditions, the measurement error of the electronic dip meter was determined to be ± 0.5 cm, which, according to van Beers (1983), is within the acceptable range. On the other hand, drainage discharges (mm day^{-1}) were measured at drain out-let points which corresponded to mid-drain spacing where WTDs were measured. Measurement of DDs was done using a bucket and a timer.

Calibration and validation of the WaSim model

Weather data records in the form of daily potential evapotranspiration (PET), rainfall and minimum and maximum temperature were obtained from the Pongola SASRI weather station located about 3 km away from the study site. Considering that the data records had so many gaps, only the weather and drainage data set (water table depth and drainage discharge) from October 1998 to September 1999 were used for calibration purposes. On the other hand, weather and drainage data from September 2011 to February 2012 were used for model validation purposes. The calibration procedure adopted in this study was done on a trial and error basis (e.g., Dayyani et al. 2009). The maximum ponding depth on the soil surface was set at half the observed depth. Having noted that observed drainage discharges were nearly 10% less than the design drainage discharge, the leaching efficiency was set at 50%, as opposed to the default 60%. In addition to that, the soil system was set to allow seepage in-flow and out-flow to concurrently exist. The rest of the soil and crop parameters, and information presented in Table 1 (including the Rosetta-estimated K_{sat} value) were left un-altered during the calibration process. Time series of WTDs and DDs were simulated, using the WaSim model after every alteration of the calibration parameters. Simulated WTDs and DDs were compared to observed WTDs and DDs. Initially, the agreement between the two data sets was assessed by visual judgments from WTD and DD hydrographs (Moriasi et al. 2007; Dayyani et al. 2009), and later on, the R^2, MAE, CRM, MPE, and NSE were applied.

Results and discussion

Performance of the rosetta to estimate K_{sat} values

Figure 2 shows the correlation of Rosetta-estimated K_{sat} values and the in situ determined K_{sat} values. Despite the Rosetta having a tendency of slightly under-estimating K_{sat} values with a CRM of 0.031, the estimated and measured K_{sat} values correlated very well, with a very strong R^2 value of 0.95 and a very small MAE value of 0.035 m day^{-1}. Further to that, the Rosetta program estimated the K_{sat} values with a very high NSE of 0.98 and a low MPE of 3.2%. Comparatively, the Rosetta-estimated K_{sat} values were slightly

Table 1 Crop and soil parameters and information used during WaSim model calibration

Parameter	Description
Soil type	Clay-loam
Drainage coefficient	5 mm day^{-1}
Rosetta generated moisture content at field capacity (%)	38
Rosetta generated moisture content at saturation (%)	55
Rosetta generated moisture content at permanent wilting point (%)	19
Rosetta-estimated saturated hydraulic conductivity (K_{sat}) (m day^{-1})	0.64
Leaching efficiency (%)	50
Observed maximum ponding depth (cm)	10
Type of crop	Sugarcane
Maximum rooting depth (cm)	140
Crop Duration to maturity (months)	11

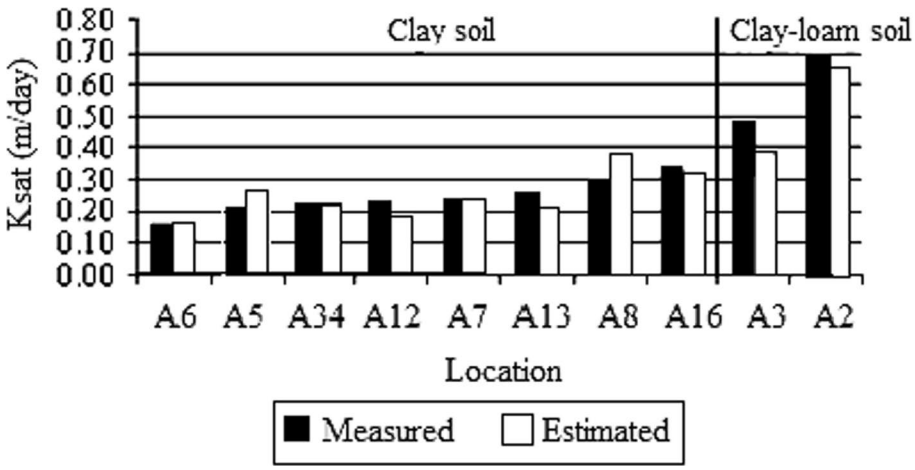

Fig. 2 A comparison of the Rosetta estimated and the measured K_{sat} values for different land units and soil types

better than those reported by Schaap et al. (2001), in which laboratory determined K_{sat} values were compared to Rosetta-estimated K_{sat} values. The good performance of Rosetta in this study was largely attributed to the comparison of in situ measured K_{sat} values to estimated K_{sat} values, as opposed to comparing laboratory determined K_{sat} values to the Rosetta-estimated values.

Soil water retention characteristic curves (SWRCCs)

Results of SWRCCs obtained by fitting measured $\theta(h)$ data to the van Genuchten (1980) soil water retention model using the RETC program are shown in Fig. 3. In all circumstances, the RETC program fitted all the measured $\theta(h)$ data very well to the van Genuchten soil water retention model, with very strong R^2 values ranging from 0.975 to 0.992. As expected, in all situations, soil moisture content decreased with an increasing soil pressure head. In all the SWRCCs, the deflection toward equilibrium pressure head was between 20 and 60 m, which mirrored those of sandy-clay and clay-loamy soils reported by Carsel and Parrish (1988), and sandy soils reported by van den Berg et al. (1997). It was encouraging to note that the soil textural class of the top soil layer at the site was also clay-loam, as reported by van der Merwe (2003). Therefore, to some extent, the trend of SWRCCs in Fig. 3 corresponded well with their respective soil textural class at the site.

Performance of WaSim model during the calibration and validation periods

A summary of the statistical performance of WaSim model both during the calibration and validation periods is presented in Table 2. Relatively small MPEs of 12.8 and 11.0% were obtained during the calibration and validation periods in simulating DDs. These results indicate that the WaSim model simulated the DDs with minimal errors. However, during the same calibration period, the WaSim model registered an MPE of 36.3%, indicating that the model was not very accurate in simulating the WTDs.

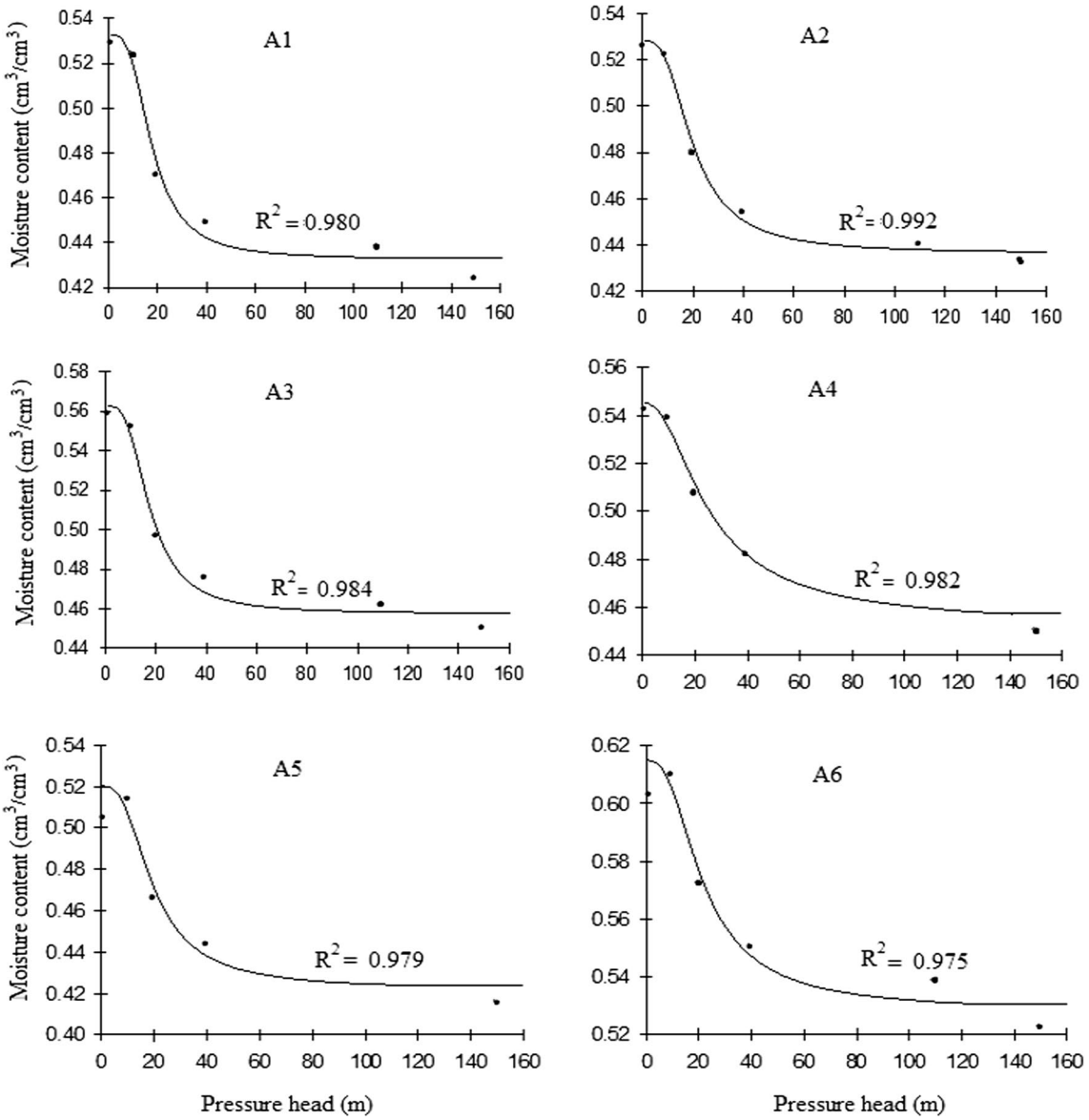

Fig. 3 Soil water retention characteristic curves, fitted using the RETC program, based on the van Genuchten (1980) soil water retention model (black shaded circle Laboratory measured,solid line Fitted)

Table 2 WaSim model performance parameters in simulating WTD and DD during calibration and validation periods

Statistical parameter	Calibration period		Validation period	
	Water table depth (cm)	Drainage discharge (mm day^{-1})	Water table depth (cm)	Drainage discharge (mm day^{-1})
R^2	0.95	0.97	0.86	0.57
MAE	15	0.4	4.9	0.3
CRM	−0.127	0.07	0.003	0.002
MPE (%)	36.3	12.8	6.0	11.0
NSE	0.94	0.97	0.98	0.76

There was, however, an improvement in the accuracy of the WaSim model in simulating WTDs during validation period (MPE = 6%). Similarly, very small MAE values of 0.40 and 0.30 mm day^{-1} were obtained both during the calibration and validation periods in simulating DDs, implying that there were very small differences between individual pairs of simulated and observed DDs. Despite that, the results in Table 2 show that WaSim model registered a high MAE of 15 cm during WTD simulation in the calibration period, as compared to the MAE value of 4.9 cm registered during WTD simulation in the calibration period. The great improvement of the MAE results during WTD simulation in the validation period gives an indication that WaSim model can reliably simulate WTDs and DDs with a reasonable accuracy even with K_{sat} data inputs estimated by the Rosetta program. The inputting of the SWRC data as opposed to using only the soil particle size data as inputs to the Rosetta, during K_{sat} estimation might have improved the K_{sat} estimation performance of Rosetta, which in turn, further resulted in the reasonably good accuracy of the WaSim model to simulate WTDs and DDs during validation.

The CRM values obtained during WaSim model validation period showed that the model perfectly simulated both the WTDs and DDs (CRM ≈ 0). On the other hand, WaSim model slightly under-estimated DDs during the calibration period (CRM > 0.0), while WTDs were slightly over-estimated (CRM < 1) during the same calibration period. The slight over-estimation of WTDs during the calibration period could be attributed to the allowing and inclusion of seepage flow from nearby naturally drained sugarcane fields during model calibration. On the other hand, the slight underestimation of DDs during the calibration period (CRM = 0.07) could be due to the slight underestimation of K_{sat} values by the Rosetta program, which consequently might have reduced groundwater flux to the drain pipes.

Simulated WTDs and DDs during calibration period correlated very well with their respective observed values, i.e., $R^2 = 0.95$ for WTDs simulation and $R^2 = 0.97$ for DDs simulation. During validation period, the model simulated WTDs and DDs with relatively moderate R^2 values of 0.86 and 0.57, respectively, giving an indication that the WaSim model performance was better during the calibration period than the validation period in simulating both WTDs and DDs. Even though R^2 values greater than 0.5 are acceptable in model simulation studies (Moriasi et al. 2007), the R^2 value of 0.57 obtained during the validation period indicated the failure of the model to simulate DDs with a high level of confidence. Skaggs (1978) highlights that subsurface drainage discharge is one of the critical determinants of the performance of subsurface drainage systems, and, as such, needs to be determined accurately. In this regard, the ability of the WaSim model to simulate DDs needs to be improved further. On the other hand, the better model performance during the calibration as compared to the performance during validation period is a common phenomenon, since in this stage, model parameters are systematically adjusted to attain the best agreement between observed and simulated values. (e.g., Hassanpour et al. 2011; Dayyan et al. 2009).

Hydrographs of simulated and observed DDs and WTDs

Pairs of hydrographs for the simulated and observed WTDs and DDs closely followed similar patterns (Figs. 4, 5, 6 and 7). Even after rainfall and/or irrigation, simulated WTD and DD hydrographs followed the curving of the observed DD and WTD hydrographs reasonably well. Despite the use of Rosetta-estimated K_{sat} values to run the WaSim model in this study, it was encouraging to note that the model simulated deeper WTDs better (Fig. 4) than the DRAINMOD model,

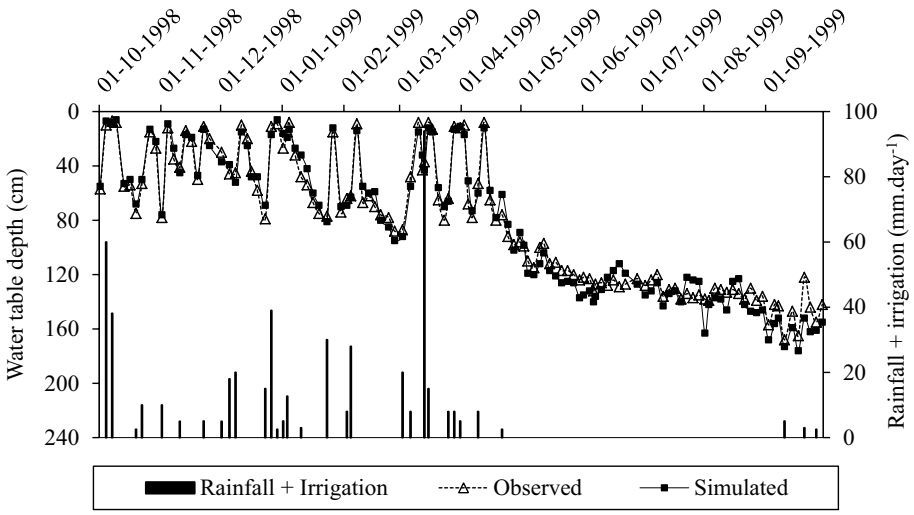

Fig. 4 Water table fluctuation during calibration period

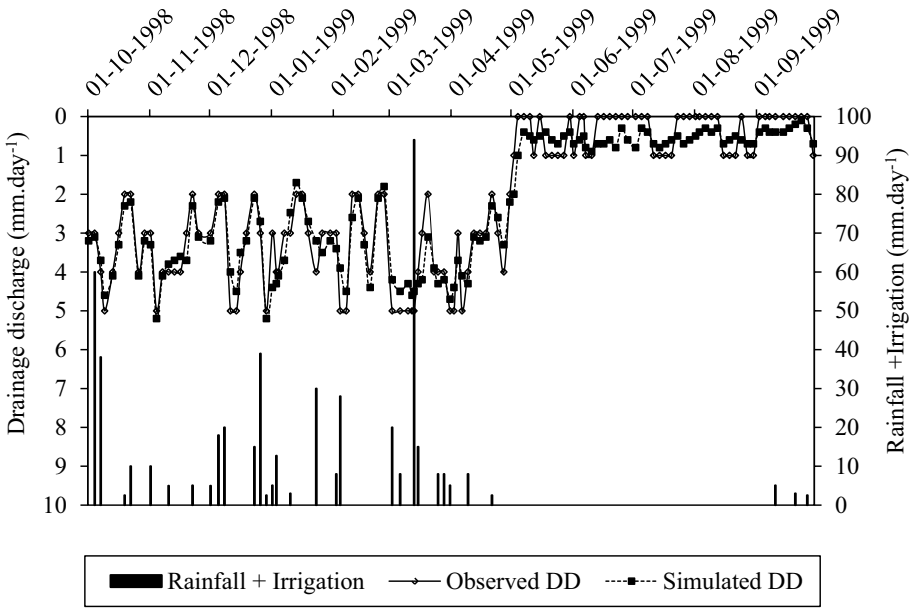

Fig. 5 Drainage discharge fluctuation the during calibration period

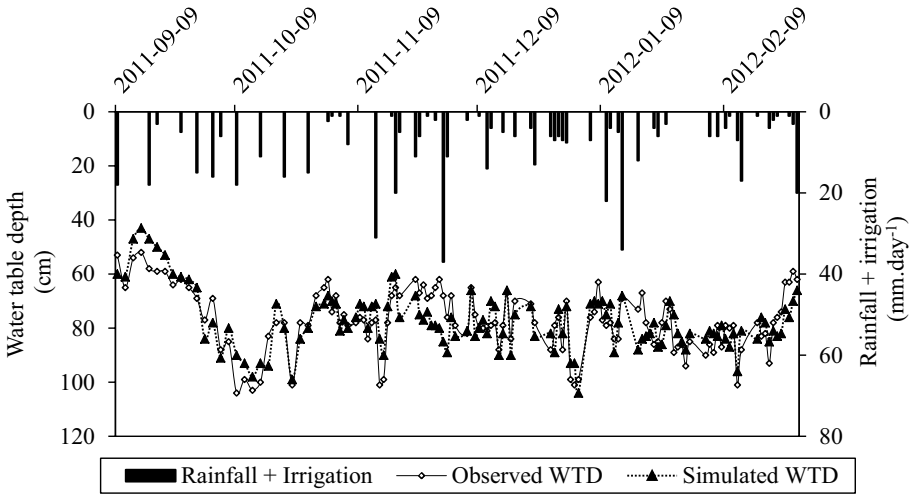

Fig. 6 Water table depth fluctuation during validation period

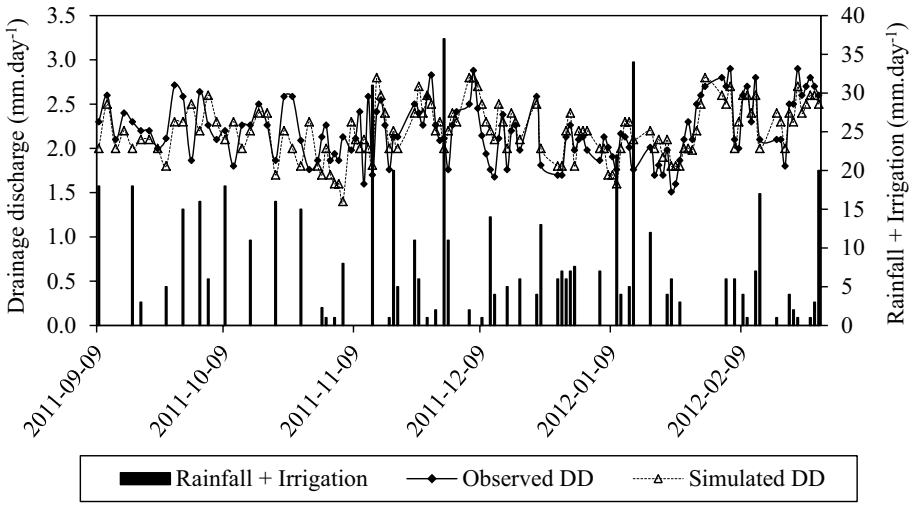

Fig. 7 Drainage discharge fluctuation during validation period

as reported by Malota and Senzanje (2015) in the same area of study. The disintegration of the soil profile into a multi soil layer water balance in the WaSim model (Fig. 1) entails treating the soil profile as a product of multiple soil layers. This approach might have described the soil profile much better as opposed to hydraulically treating the whole soil profile as a single homogenous entity.

A comparison of R^2 values obtained in this study to those of Malota and Senzanje (2015), where DRAINMOD was tested to simulate the fluctuation of WTDs and DDs in the same area, indicates that DRAINMOD model predicted WTDs slightly better than the WaSim model during the validation period. In particular, the WaSim model failed to accurately simulate DDs. The possible explanation for this disparity could be the use of in situ K_{sat} values as soil hydraulic inputs in the DRAINMOD model, as opposed to the use of Rosetta-estimated K_{sat} values in WaSim model adopted in this study. Considering that most hydrological models are sensitive to K_{sat} values (Skaggs 1978), whenever possible, Dayyani et al. (2009) and Salazar et al. (2008) recommend the use of PTF-estimated K_{sat} values as inputs to hydrological models, only when in situ determined K_{sat} values are not available.

Concluding remarks and recommendations

This study evaluated the reliability of the WaSim model to simulate WTDs and DDs using K_{sat} values estimated by the Rosetta computer program. The general performance of the WaSim model during the validation period suggest that the model cannot reliably be used as a subsurface drainage design tool in the study area. The model failed to simulate DDs with a high level of confidence ($R^2 = 0.57$). The results showed that the use of Rosetta-estimated K_{sat} data as inputs to the WaSim model compromised its performance and applicability, both as a subsurface drainage design tool, and for the development of artificial subsurface drainage design criteria. This study, therefore, recommends further improvement on the calibration of the WaSim model to accurately simulate both WTDs and DDs. Also, in the absence of other means of measuring K_{sat}, caution must taken when using the Rosetta-estimated K_{sat} data as inputs to the WaSim model for the design and analysis of artificial subsurface drainage systems in the KwaZulu-Natal Province, South Africa.

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Declarations

Conflict of interest All authors have agreed to submit this manuscript to the journal of Applied Water Science.

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