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Simulation of water distribution under surface dripper using artificial neural networks

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A B S T R A C T

Predicting the wetting pattern of a dripper helps in the proper design of the drip irrigation system. An artificial neural network predictor model was developed based on the data from the well-tested model HYDRUS 2D/3D. The simulation data grid from HYDRUS was converted to simpler 3-variables vectors of wetting ellipses. The output vectors contain the radii in x and z directions and the center's location in the z direction. The simulations were performed for several textural classes, infiltration times, emitter's discharges, hydraulic models, and other features. After training the neural network, the testing dataset showed a correlation of 0.93–0.99, and the tested patterns showed high similarity to the HYDRUS outputs. Additionally, the paper provided solutions for the problem of simulating larger flow emitters where the flux exceeds the soil's hydraulic conductivity and the problem of converting HYDRUS outputs to easy-to-use vectors of three parameters representing specific moisture content at a particular time. This work tried a set of 51 input variables' permutations suggesting the best set of top results. The best trained neural network is freely available for the benefit of researchers and for future development. The sensitivity analysis of the input variables showed that the wetting pattern is mostly affected by time of infiltration, emitter discharge, and the saturated hydraulic conductivity. Future developments of the model are promising by increasing the training data extremes and possibly by adding more features like emitter's depth for the subsurface drippers.

1. Introduction

Drip irrigation system offers the highest water conservation among all other irrigation systems. The main reason of such conservation is that it limits the wetted zone to about 30% of that the other systems do, hence, reduces deep percolation, surface runoff, and evaporation from the soil surface (Brouwer et al., 1988). The shape of the wetted part of the soil root zone is called the Wetting Pattern (WP). The WP is a partially saturated region with truncated-ellipsoid shape whose dimensions depend on several factors. These factors depend on the soil (texture, compaction, hydraulic conductivity, etc.), the plant (type, age, roots, etc.), the irrigation system's features (dripper discharge, application frequency, etc.), and the climatic conditions (temperature, relative humidity, etc.) (Bhatnagar and Chauhan, 2008; Peries et al., 2007). Understanding the wetting pattern features is very important to achieve the reliable design of drip irrigation systems as well as for efficient management of natural resources (Lazarovitch et al., 2009; Lubana and Narda, 2001).

Several approaches to simulate the wetting pattern were performed; these were either empirical, analytical, or numerical (Kandelous and Šimůnek, 2010a). Empirical approaches use regression tools to derive an equation based on the results of well-controlled experiments (e.g. Malek and Peters, 2010). Analytical approaches use mathematical approximations to the modeled phenomena so that the governing equation can be solved with some easy calculations (e.g. Cook et al., 2003; Kandelous et al., 2008). On the other hand, numerical approaches (Arbat et al., 2013; e.g. Šimůnek et al., 2011) use the same governing equation as the analytical approaches, but they solve it numerically (by methods like finite element or finite difference) with almost no approximation or simplification. Unlike numerical approaches, both analytical and empirical approaches are fast and easy to solve, but their results are less precise than the results of the empirical approaches. Additionally, it worth to notice that the analytical models are useful in understanding principles than other approaches, but because of the spread of computers and other smart devices, the numerical methods became much more attractive as they could handle more complex and realistic situations (Kalogirou, 2007).

One of the most famous two-dimensional numerical models is the

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Nomenclature

θ	volumetric water content, L^3L^{-3}
t	time, T
h	soil water pressure head, L
x	horizontal coordinate
z	vertical coordinate
K	unsaturated hydraulic conductivity, LT^{-1}
K_s	saturated hydraulic conductivity, LT^{-1}
S	sink term representing root water uptake, $L^3L^{-3}T^{-1}$
θ_r	residual water content, L^3L^{-3}
θ_s	saturated water content, L^3L^{-3}
$\boldsymbol{\alpha}$	empirical parameter for hydraulic models, L^{-1}
$\boldsymbol{n}$	empirical parameter for hydraulic models, –
Φ	soil-water flux, LT^{-1}
q	emitter discharge, L h^{-1}
m	number of emitters per meter, –
r	radius, L
Φ_{adj}	adjusted soil-water flux, LT^{-1}
η	wetting ellipse center's location in z direction, L
β	a number from 1 to 9 representing wetting ellipse from near dryness to near saturation, –
δ	wetting ellipse radius in x direction, L
ψ	wetting ellipse center's location in x direction, L
γ	Wetting ellipse radius in z direction, L
θ_β	current moisture content, L^3L^{-3}
θ_x, θ_n	maximum and minimum moisture content, L^3L^{-3}
θ_{eff}	effective saturation, –
τ	time factor, –
T_i	infiltration time, T
T_{ts}	current time-step, T
T_e	time at the end of redistribution, T
N_s	number of records in the training dataset
N_i, N_o	number of input and output neurons
ν	number of interconnected neurons in a layer
MFG	Method(s) of Features' Grouping
ANN	Artificial neural networks
GIT	A quick name for the version control website GitHub.com

HYDRUS (2D/3D) software package (Šimůnek et al., 2011). The model is a finite element model for simulating the two- or three-dimensional movement of water, heat, and multiple solutes in variably saturated media. The model numerically solves the Richards equation for saturated–unsaturated water flow and convection–dispersion type equations for heat and solute transport. HYDRUS was well-tested by many investigators for surface or subsurface drip irrigation simulation (Skaggs et al., 2004; Cook et al., 2006; Arbat et al., 2008; Kandelous and Šimůnek, 2010a, 2010b; Ramos et al., 2012; Abou-Lila et al., 2013; Elnesr et al., 2013; Liu et al., 2013). The good results of HYDRUS validation increases its reliability and trustfulness especially for no-plant simulation (Mmolawa and Or, 2003; Zhou et al., 2007)

Despite the benefits of the numerical solutions, they are not always easy-to-use approaches. They are, however, very sensitive to the boundary and initial condition, they may be unstable if over-relaxation occur, they may have difficulties with speed and possibility of convergence, the precision is directly-proportional to the required hardware resources, and it needs a higher level of human skills than the analytical models (Neufeld, 2010; Toombes and Chanson, 2011). Hence, we need a more robust approach that leads to more realistic and fast simulations; this might be achieved by the artificial intelligence approaches. In these approaches, the models attempt to act like the human brain that collects several input features that frequently appear together, and link them to the result or output through a complex nervous system that learns and improves its efficiency over time. This imitation to the human brain is called the artificial neural networks (ANN). Several works were published showing attempts to simulate the in-soil flow of water and solutes.

One of the earliest attempts was the work of Li et al. (2004) who combined laboratory experiments with the ANN in simulating the distribution of nitrate fertigated by a dripper; they concluded that the ANN models are reasonably accurate and can provide an easy and efficient means of estimating nitrate distribution. Lazarovitch et al. (2009) used the ANN approach in predicting water distribution around subsurface drip irrigation. They used HYDRUS simulations (Šimůnek et al., 2011) as the reference to water distribution, and they tested three scenarios of input-output combinations concluding that prediction using moment analyses is probably the most robust and gives an adequate picture of the subsurface dripper water distribution. Later, Hinnell et al. (2010) used this approach to develop a Microsoft Excel's model that depends on moment analysis to draw contours that are a close representation of the actual wetting pattern.

1.1. Aim of the work

The objective of this work is to develop a different neural network's approach to simulating the wetting pattern from a surface dripper, with the various timings of infiltration and redistribution, different soil textural classes, different soil-water retention models, etc. Additionally, we aimed to use the developed model to evaluate the contribution of each variable to the drip wetting pattern.

2. Material and methods

2.1. Governing equations of water movement in soil

We used HYDRUS (2D/3D) package to simulate soil-water distributions under a dripping point source. The model numerically solves the Richards equation for variably-saturated water flow in soils. The Richards governing equation in two-dimensional coordinates is as follows (Tian et al., 2011):

$$\frac{\partial\theta}{\partial t} = \frac{\partial}{\partial x}\left[K(h)\frac{\partial h}{\partial x}\right] + \frac{\partial}{\partial z}\left[K(h)\frac{\partial h}{\partial z}\right] - \frac{\partial K(h)}{\partial z} - S(h) \quad (1)$$

Table 1
Properties of the sample soil textures that were used in the simulations.

Texture	θ_r	θ_S	K_s (cm/min)	Sand (%)	Clay (%)	Silt (%)	α (1/cm)	n	Abbrev.	Plaut Index
Sand	0.045	0.430	0.495000	93	1	6	0.145	2.68	Snd	19
Loamy Sand	0.057	0.410	0.243194	85	5	10	0.124	2.28	LSn	18
Sandy Loam	0.065	0.410	0.073681	65	15	20	0.075	1.89	SnL	13
Loam	0.078	0.430	0.017333	45	15	40	0.036	1.56	Lom	10
Silt	0.034	0.460	0.004167	10	5	85	0.016	1.37	Slt	8
Sandy Clay Loam	0.100	0.390	0.021833	60	25	15	0.059	1.48	SCL	6
Clay Loam	0.095	0.410	0.004333	35	35	30	0.019	1.31	ClL	5
Sandy Clay	0.100	0.380	0.002000	55	40	5	0.027	1.23	SnC	3