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ORIGINAL ARTICLE

Predicting the spatial distribution of water applied by subsurface drip in clay soil[1]

Predição da distribuição espacial da água aplicada por gotejamento subsuperficial em solo argiloso

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HIGHLIGHTS:
The tested models are suitable for simulating water spatial distribution by drippers operating at depth in soil columns.
The installation depths of the drippers do not affect the estimation of soil moisture by the models evaluated.
SLIDE 6.0 outperformed SPSS 2.0 and polynomial regression models for simulating soil water distribution.

ABSTRACT: In subsurface drip irrigation systems, knowledge of the three-dimensional advancement of water in the soil is essential for selecting emitter spacing and installation depth. This research aimed to develop and test different mathematical models to estimate water distribution in the soil under subsurface drip irrigation. The experiment was set up in a completely randomized design with four replicates. The experimental arrangement was of split-plot in time, with different dripper installation depths in the plots (0, 5, 10, 15, 20, 25, and 30 cm) and in the subplots irrigation application times (0, 60, 120, 180, and 240 min). Three models (SLIDE 6.0, polynomial regression, and SPSS 2.0) were constructed to estimate the water distribution in the soil profile. All models showed statistical indexes within acceptable ranges. In comparison, the model generated in the numerical software SLIDE 6.0 was the one that presented the best performance, followed by SPSS 2.0 and polynomial regression. The generated models were efficient and simple, producing good results in predicting the water distribution in the soil profile under the studied conditions.

Key words: soil moisture, buried drip irrigation, localized irrigation, irrigation modeling

RESUMO: Em sistemas de irrigação por gotejamento subsuperficial, o conhecimento do avanço tridimensional da água no solo é essencial na seleção do espaçamento e profundidade de instalação dos emissores. O objetivo desta pesquisa foi desenvolver e testar diferentes modelos matemáticos para estimar a distribuição de água no solo sob irrigação por gotejamento subsuperficial. O experimento foi montado em delineamento inteiramente casualizado com quatro repetições. O arranjo experimental foi de parcelas subdivididas no tempo, tendo nas parcelas diferentes profundidades de instalação de gotejadoras (0, 5, 10, 15, 20, 25 e 30 cm) e nas subparcelas tempos de aplicação da irrigação (0, 60, 120, 180 e 240 min). Foram construídos três modelos (SLIDE 6.0, regressão polinomial e SPSS 2.0) para estimar a distribuição de água no perfil do solo. Todos os modelos apresentaram índices estatísticos dentro de faixas aceitáveis. Na comparação, o modelo gerado no software numérico SLIDE 6.0 foi o que apresentou melhor desempenho, seguido do SPSS 2.0 e regressão polinomial. Os modelos gerados foram eficientes e simples, apresentando bons resultados na predição da distribuição de água no perfil do solo para as condições estudadas.

Palavras-chave: água no solo, gotejamento enterrado, irrigação localizada, modelagem da irrigação

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Introduction

Subsurface irrigation systems have become increasingly popular in recent decades. With proper design and precise management, this system can provide more efficient irrigation than surface irrigation (Shiri et al., 2020). However, progress is still needed, for which it is essential to understand water movement in the soil better (Kermani et al., 2019; Ravikumar et al., 2021).

Knowing soil moisture distribution can reduce water application amounts and provide useful information for determining the ideal distance between laterals and emitters (Karimi et al., 2020). The moisture distribution pattern is a function of the soil's physical characteristics, the flow rate, the water application mode, and the depth and spacing of the emitters (Al-Ogaidi et al., 2016; Elnesr & Alazba, 2019; Vigo et al., 2020).

The distribution of water can be obtained by field measurements, with experimental physical models in the laboratory, and through mathematical models (Araújo et al., 2020; Ravikumar et al., 2021). Based on the Richards equation, complex models require numerical methods due to their non-linear nature but have limitations as they require detailed information and high computational performance (Moncef & Khemaies, 2016). Analytical models are more practical due to simplifying assumptions (Liu & Xu, 2018; Moncef & Khemaies, 2016), and empirical models with field data are also used but can have limitations in different soils and by disregarding initial moisture conditions (Muñoz et al., 2022). So, researchers have used experiments in controlled environments and software such as SLIDE to obtain more accurate models (Rocscience Inc., 2010).

This study hypothesized that it is possible to estimate the evolution of the temporal distribution of water in the soil with an empirical model that includes the soil's physical properties and irrigation characteristics. This research aimed to develop and test different mathematical models to estimate water distribution in the soil under subsurface drip irrigation.

Material and Methods

The experiment was conducted in the experimental area of the Hydraulics Laboratory belonging to the Water Resources Reference Center (CRRH) of the Universidade Federal de Viçosa (UFV), Minas Gerais, Brazil. In the experiment, 28 soil columns were set up with dimensions of 40 cm in diameter, 55 cm in height, and 70 liters in volume (Figure 1). The columns were filled with soil collected from a ravine on the UFV campus. To achieve soil stability and moisture distribution closer to natural, there was a rest period of seven days before starting the irrigation events. Therefore, the moisture content values were relatively similar in all replicates. Soil samples were taken to determine the physical properties, such as texture, density, and hydraulic conductivity of the saturated soil. The physical properties of the soil under study are shown in Table 1.

The experiment was set up in a completely randomized design with four replicates. The experimental arrangement was split-plot in time, with different dripper installation depths in

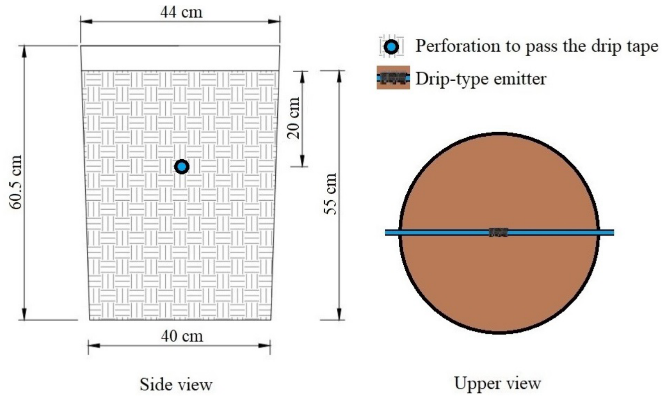


Figure 1. Demonstrative drawing of the soil columns used in the experiment

Table 1. Physical properties of the soil used in the experiment

Features	Method	Value
Soil density (g cm^{-3})	Volumetric ring (EMBRAPA, 2017)	1.06
Saturated conductivity (m d^{-1})	Permeameter (EMBRAPA, 2017)	5.56
Coarse sand (kg kg^{-1})	Sieve and sedimentation (EMBRAPA, 2017)	0.307
Fine sand (kg kg^{-1})	Sieve and sedimentation (EMBRAPA, 2017)	0.137
Silt (kg kg^{-1})	Pipette (EMBRAPA, 2017)	0.128
Clay (kg kg^{-1})	Pipette (EMBRAPA, 2017)	0.428
Soil texture	United States (2014)	Clay
Soil classification	United States (2014)	Oxisol

the plots and irrigation application times in the sub-plots. The drip strips were installed at seven depths in the soil column: 0, 5, 10, 15, 20, 25, and 30 cm. Only one dripper was installed in each soil column, inserting it at the center point in a horizontal direction. The drippers used were of the Amnondrip model and manufactured by NaanDanJain™, operating at a pressure of 20 mwc (meters of water column) and a flow rate of 1.6 L h^{-1}. Irrigation was carried out for four hours with soil samples taken at 60-minute intervals (0, 60, 120, 180, and 240 min). The installation depths of the drippers and the irrigation times were chosen to serve as a basis for managing the irrigation of different crops (Dashtgol et al., 2022; Santos et al., 2016).

The sampling points were located along a grid, taking the location of the emitter as the central axis, and from this point, 20 cm was sampled horizontally. The 20 cm is equivalent to a bulb diameter of 40 cm, a common size for clayey soil (Pinto et al., 2022; Souza et al., 2018). The thermogravimetric method was used to determine the soil moisture. For each replicate, soil samples were collected with an auger from the soil profile at 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50 cm.

Three different models were implemented using moisture data measured in the field to predict water distribution in the soil profile. The first model was generated using SLIDE 6.0 software, the second using polynomial regression using Excel, and the third using Statistical Package for the Social Sciences (SPSS) 2.0 software.

Using the data collected in the field experiments, the models were based on the temporal and spatial distribution of volumetric humidity. The data set was divided into two parts: training and testing. Thus, in each simulation referring to the different depths of installation of the irrigation drip, the moisture data from the respective depths was hidden to draw up the projects.

Water flow was simulated using SLIDE 6.0 software (Rocscience Inc., 2010). The software used initial soil moisture data and their respective matric potentials, which were calculated using the van Genuchten equation (Eq. 1).

$$\theta = \theta r + \left(\theta s - \theta r\right)\left[\frac{1}{1+\left(\alpha\Psi\right)^{n}}\right]^{m} \qquad (1)$$

where:

θ - current volumetric soil moisture (cm^3 cm^{-3});

θr - residual volumetric moisture (cm^3 cm^{-3});

θs - saturated volumetric moisture (cm^3 cm^{-3});

Ψ - matric potential (kPa); and,

m, n, α - fit parameters of the van Genutchen model.

It is worth noting that in the development of the model, the initial soil moisture was taken into account, as reported by Shiri et al. (2020), as an essential factor in determining the water distribution pattern. Therefore, the initial conditions of the simulations were defined according to the soil moisture data measured in the field using the gravimetric method before the irrigations began, assuming that the matric potential depended only on depth. As for the start of irrigation, a water source was considered at a point in the middle of the matrix corresponding to the emitter installed in the field.

Next, a 40 cm x 54 cm grid was drawn, representing the dimensions of the soil columns installed in the field. The soil moisture values at the depths of 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50 cm were those obtained in the field before the irrigation events. Different emitter installation depths were simulated within the grid, just as the driplines were arranged in the field (0, 5, 10, 15, 20, 25, and 30 cm). The model was discretized, creating a grid with 5,000 triangular elements with six nodes, including the soil water retention curve parameters and the hydraulic conductivity value of the saturated soil.

Two flow regime modules were configured: stationary and transient. In the stationary regime, the moisture data collection points were configured with negative pressure, representing the matric potential. The emitter points were configured as a water source with a flow rate of 1.6 L h^{-1}. In the transient module, the boundary conditions were left unknown, and the emitter location point was configured to simulate a four-hour irrigation event.

After the configurations, the software suggested different models for each drip installation depth and water distribution in the soil columns, analyzing a central point (near the emitter) and another 20 cm away from this point.

An empirical polynomial regression model was suggested to simulate water distribution considering the different installation depths of the emitters (0, 5, 10, 15, 20, 25, and 30 cm). Models were suggested for a central point (near the emitter) and a point 20 cm away from the central point. As with the previous model, the data collected in the field during the irrigation events and the initial soil moisture before the events were used.

A simple linear regression model was also created in SPSS 2.0, with the dependent variable being volumetric humidity and the independent variable being the installation depth of the emitters in the field (0, 5, 10, 15, 20, 25, and 30 cm), generating an equation for a central point (near the emitter) and for a point 20 cm away from the central point.

The results of the models were evaluated using five statistical metrics: the coefficient of determination (R^2), the root mean square error (RMSE), the mean absolute error (MAE), the mean bias error (MBE), and the Nash-Sutcliffe model efficiency coefficient (NS).

Results and Discussion

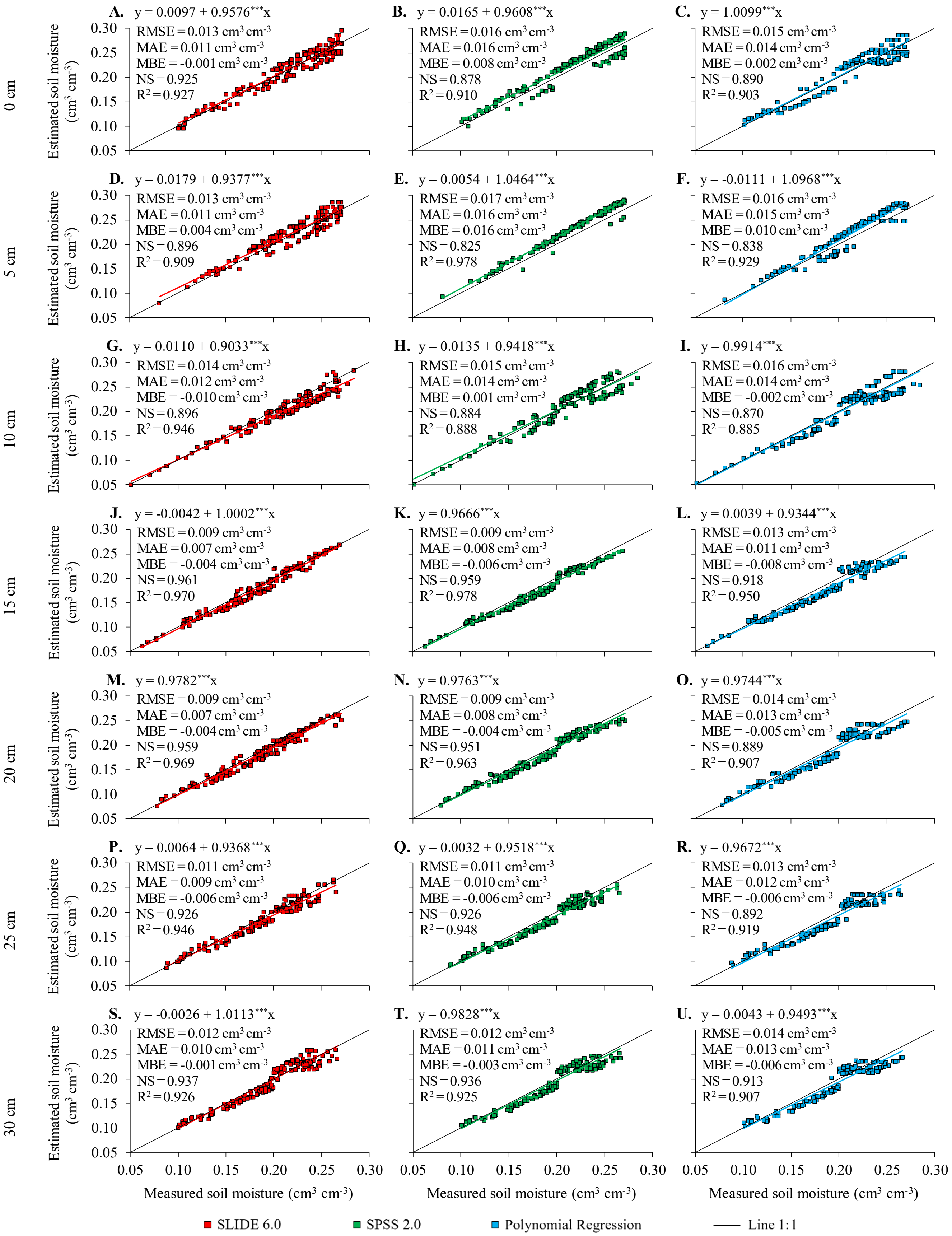
The dispersion between the observed and estimated soil moisture data and the results of the statistical analysis for each model and dripper installation depths are presented in Figures 2A to U for the soil collected at the central point of the columns and in Figure 3A to U with the soil collected 20 cm away from the central point. Visually, there was little dispersion in the data, showing that the models were accurate. This can be confirmed by the high coefficient of determination (R^2) values, higher than 0.885 for all scenarios. The lowest R^2 value was obtained with soil moisture collected in the center of the column, with the emitter installed at a depth of 10 cm, and using the polynomial regression model (Figure 2I). The highest R^2 value was 0.980, obtained when soil moisture was collected 20 cm away from the center of the column, with the emitter installed 5 cm deep and using the SPSS 2.0 model (Figure 3E). Predictive models with high R^2, that is, high accuracy, can improve their prediction performance further when calibrated (Ferreira et al., 2019).

Soil moisture in the central part showed higher values than in points 20 cm away from the central point. The difference in soil moisture between the two points analyzed was greater at shallower depths. This indicates that the moistening front showed a reduction in vertical progression.

Table 2 summarizes the values of the statistical metrics used to compare the observed and estimated soil moisture. Table 2 shows the average values of the statistical metrics for each variable used in the study. On average, the R^2 of the model generated in SLIDE 6.0 was higher than the SPSS 2.0 model, which, in turn, was higher than the polynomial regression model.

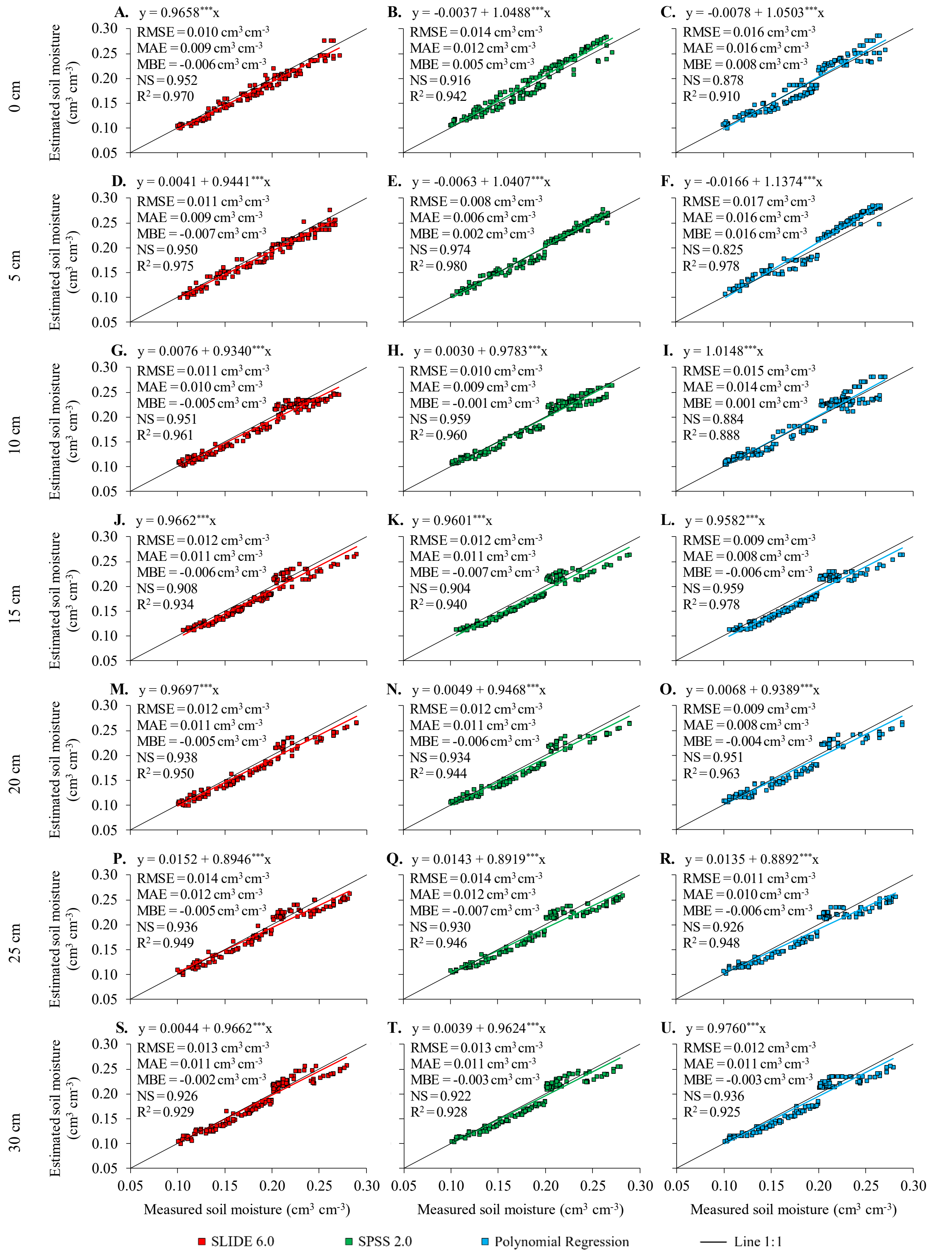
Regarding the location of the evaluated point, the central point had a lower average R^2 than the point 20 cm away (Table 2). Solat et al. (2021) also found better-simulated results at the points furthest from the emitter, using the Hydrus software to model the distribution of wet bulbs on sloping land. Arraes et al. (2019) also verified this behavior for the points furthest from the emitter. They attributed these results to the fact that at the end of the study period, the water had not yet been distributed throughout the domain.

In general, the prediction models underestimated soil moisture, according to the dispersion of the data below the 1:1 line and the MBE values (Figures 2 and 3 and Table 2). Although this underestimate is small, approximately 0.93%,



RMSE - Root mean square error; MAE - Mean absolute error; MBE - Mean bias error; NS - Nash-Sutcliffe efficiency. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Figure 2. Moisture at the center point of soil columns estimated by different models and at different depths of dripper installation: 0 cm, SLIDE 6.0 (A); 0 cm, SPSS 2.0 (B); 0 cm, polynomial regression (C); 5 cm, SLIDE 6.0 (D); 5 cm, SPSS 2.0 (E); 5 cm, polynomial regression (F); 10 cm, SLIDE 6.0 (G); 10 cm, SPSS 2.0 (H); 10 cm, polynomial regression (I); 15 cm, SLIDE 6.0 (J); 15 cm, SPSS 2.0 (K); 15 cm, polynomial regression (L); 20 cm, SLIDE 6.0 (M); 20 cm, SPSS 2.0 (N); 20 cm, polynomial regression (O); 25 cm, SLIDE 6.0 (P); 25 cm, SPSS 2.0 (Q); 25 cm, polynomial regression (R); 30 cm, SLIDE 6.0 (S); 30 cm, SPSS 2.0 (T); and 30 cm, polynomial regression (U)



RMSE - Root mean square error; MAE - *Mean absolute error*; MBE - Mean bias error; NS - Nash-Sutcliffe efficiency. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Figure 3. Moisture at a point 20 cm away from the center of the soil columns estimated by different models and at different depths of dripper installation: 0 cm, SLIDE 6.0 (A); 0 cm, SPSS 2.0 (B); 0 cm, polynomial regression (C); 5 cm, SLIDE 6.0 (D); 5 cm, SPSS 2.0 (E); 5 cm, polynomial regression (F); 10 cm, SLIDE 6.0 (G); 10 cm, SPSS 2.0 (H); 10 cm, polynomial regression (I); 15 cm, SLIDE 6.0 (J); 15 cm, SPSS 2.0 (K); 15 cm, polynomial regression (L); 20 cm, SLIDE 6.0 (M); 20 cm, SPSS 2.0 (N); 20 cm, polynomial regression (O); 25 cm, SLIDE 6.0 (P); 25 cm, SPSS 2.0 (Q); 25 cm, polynomial regression (R); 30 cm, SLIDE 6.0 (S); 30 cm, SPSS 2.0 (T); and 30 cm, polynomial regression (U)

Table 2. Values of statistical metrics for comparing soil moisture observed and estimated by different models at different collection points and installation depths of drippers

Factor	Variable	R^2	MBE	MAE	RMSE	Nash-Sutcliffe
				(cm^3 cm^{-3})		
Model	SLIDE 6.0	0.9472	-0.0040	0.0100	0.0117	0.9329
	SPSS 2.0	0.9452	-0.0007	0.0111	0.0123	0.9213
	Regression	0.9279	-0.0006	0.0125	0.0136	0.8978
Distance from the center point of the column (cm)	0	0.9325	-0.0014	0.0115	0.0129	0.9080
	20	0.9477	-0.0022	0.0109	0.0121	0.9266
Drip installation depth (cm)	0	0.9270	0.0028	0.0130	0.0140	0.9065
	5	0.9582	0.0068	0.0122	0.0137	0.8847
	10	0.9213	-0.0027	0.0122	0.0135	0.9073
	15	0.9583	-0.0062	0.0093	0.0107	0.9348
	20	0.9493	-0.0045	0.0097	0.0108	0.9370
	25	0.9432	-0.0060	0.0108	0.0123	0.9227
	30	0.9233	-0.0028	0.0112	0.0127	0.9283

RMSE - Root mean square error; MAE - M*ean absolute error*; MBE - Mean bias error; NS - Nash-Sutcliffe efficiency

this error could impact irrigation management, where more water will be supplied than is required. This will certainly also affect crop development and, if these two problems are added together, could cause financial losses.

Zhang et al. (2013), in their research using the HYDRUS-2D software, concluded that the underestimation of soil moisture occurred due to hysteresis. This same situation may have occurred in the present study, as the parameters related to the soil retention curve were acquired after the initial construction of the curve using the Richards extractor equipment. In this process, the samples were already saturated. However, in the field environment, the samples were progressively moistened through the gradual application of water during irrigation. This resulted in a gradual reduction in the tension applied to the soil columns. Therefore, a disparity may have arisen in the shape of the characteristic curve, leading to discrepancies in the gravimetric moisture values.

To overcome this problem, new models that consider hysteresis must be created. However, it is known that there is a high complexity of theories about hysteresis, as the expansion and contraction mechanism in clays is complex and influenced by several factors. Thus, the complexity of the numerical values of solutions for unsaturated water flow problems is perceived, which is substantially increased by boundary conditions when hysteresis is included (Mualem, 1984).

Some researchers have also mentioned that the underestimation of gravimetric moisture may be attributed to overestimating the evaporation rate (Ursulino et al., 2019). However, in the context of this study, the exposure period of the soil columns was not prolonged enough to significantly impact evaporation. Likewise, a study conducted by Turco et al. (2017) also showed an underestimation of the soil's retention capacity, which possibly occurred in the present study, given the presence of variations in the distribution of clay in the soil columns. As a result, different moisture conditions in the field may have emerged, even when comparing the identical depth for installing the drip system and the equivalent irrigation time. It is important to note that this variable was not incorporated into any modeling approaches in this study.

For the SPSS 2.0 and polynomial regression models, there were also overestimates in the superficial soil layer (up to 10 cm) and underestimates in the other layers (Figures 2 and 3). This phenomenon can be attributed to the complexity of the soil, resulting from the heterogeneity of the layers in the soil columns. However, this variation is not considered in any of the models evaluated. This is supported by Ghazouani et al. (2019), who conclude that the inaccurate estimation of the amount of water in the soil is related to an imperfect representation of the soil's hydraulic properties for the specific layer. Therefore, by neglecting the physical-hydraulic properties of the soil, as well as the discrepancies between its layers, these models can provide results that are discrepant concerning the real situation.

The limitations associated with overestimates or underestimates stem from the complexity of the water distribution process in the soil, the variation in water input distribution, and the interaction among the processes occurring in the soil, water, and atmosphere. These limitations highlight the need to improve the input parameters for a more accurate fit of the model (Silva et al., 2015). Additionally, it is important to note that the model does not consider local variations or discontinuities between soil layers. This can result in overestimating the flow in low-permeability layers or underestimating in high-permeability layers (Lu et al., 2021).

Among the models tested, the one generated in SLIDE 6.0 software showed the lowest error according to the MAE and RMSE statistical metrics (Table 2). This was followed by the lowest errors in the SPSS 2.0 and polynomial regression models. Generally, numerical software can estimate the water distribution area in the soil profile with adequate precision. One of the reasons for this satisfactory performance is that several influential variables are considered (according to previous studies), and this technique can relate inputs to outputs with a strong recognition pattern (Karimi et al., 2020). In addition, one can add the software's logical understanding of soil complexity based on governing flow equations.

The Nash-Sutcliffe (NS) efficiency coefficient shows how good the model is compared to the others (Ghazouani et al., 2019; Muñoz et al., 2022). According to this metric, the best models were SLIDE 6.0, SPSS 2.0, and polynomial regression, in this sequence. The model generated by SLIDE 6.0 outperformed the others because it considers more input variables and provides a better understanding of the soil environment. In this respect, the SLIDE 6.0 model considers soil characteristic parameters, including bulk density and soil hydraulic conductivity, which can provide a better understanding of the complexity of water distribution in the soil profile. In the other models, these parameters were not considered, and only the volumetric soil moisture was considered.

Even though SLIDE 6.0 showed the best performance, it must be acknowledged that the other models studied also predicted the behavior of water distribution in the soil profile with satisfactory performance. According to Table 2, the SPSS 2.0 and polynomial regression models showed low MBE, MAE, and RMSE values (close to zero) and high R^2 values (close to one). In addition, based on statistical metrics, the models showed good ability to simulate wetting patterns in subsurface systems when compared to previous literature (Al-Ogaidi et al., 2016; Karimi et al., 2020; Karimi et al., 2021; Sierra et al., 2021).

The results could have been even better if the soil in this study had a sandy texture, probably. Comparing soils of different textures, Elnesr & Alazba (2019) and Karimi et al. (2020) reported that the performance of the models in soils with a sandier texture (approximately 70% sand) was better than in soils with a clayier texture (more than 30% clay). According to the authors, clay soils such as those used in this study have low hydraulic conductivity, making it difficult to model water distribution. In addition, preferential flows can occur in clay soils, and the models may not be able to simulate them.

In summary, the results show that the proposed models perform adequately under different combinations of volumetric humidity data and emitter installation depth. As the models' initial conditions align with field conditions, the suggested results can be applied directly to design and implementation aspects. In addition, the regression coefficients of the proposed models are general and can be used for similar soil types, flow rates, and emitter types. The main motivation for this research was to provide a reliable technology based on an easy-to-understand methodology and use basic computing to simulate the water distribution of subsurface drip irrigation systems.

Considering that this research was carried out for a specific condition (subsurface drip irrigation system with continuous mode, for homogeneous soil, in columns), it is interesting to carry out water distribution simulations for drip irrigation systems with pulse mode, different layers of the soil profile, and over larger areas, using different approaches, such as machine learning. Another necessary approach is the use of wastewater since the subsurface irrigation system must be recommended to minimize the risks of plant, atmosphere, and irrigator contamination.

Conclusions

1. The models generated proved suitable and applicable for simulating water distribution from drippers installed at different soil depths in soil columns under experimental conditions.

2. When comparing them, the model generated by SLIDE 6.0 proved superior to SPSS 2.0, which was superior to polynomial regression.

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