

Article

Modeling Water and Salt Dynamics by HYDRUS 2D/3D Under Drip- and Surface-Irrigated Carrot in Arid Regions

Warda Tlig ^{1,2,3}, Dario Autovino ¹, Fathia El Mokh ², Kamel Nagaz ² and Massimo Iovino ^{1,*}

¹ Department of Agricultural, Food and Forest Sciences, University of Palermo, 90128 Palermo, Italy; tlig.warda@gmail.com (W.T.); dario.autovino@unipa.it (D.A.)

² Drylands and Oasis Cropping Laboratory, Arid Regions Institute, Medenine 4119, Tunisia; elmokh.fa@gmail.com (F.E.M.); kamelnagaz@yahoo.com (K.N.)

³ National Institute of Agronomy, University of Carthage, Tunis 1082, Tunisia

* Correspondence: massimo.iovino@unipa.it

Abstract

Understanding the distribution of water and salt in the crop's root zone and predicting future soil degradation requires specific monitoring to establish guidelines for irrigation management and system performance. Two field experiments were conducted in the arid region of Southern Tunisia to assess soil water and salt dynamics under surface- and drip-irrigated carrots using HYDRUS 2D/3D simulations in the 2017–2018 and 2018–2019 crop seasons. The soil water contents and bulk soil electrical conductivities were measured at three distinct soil layers: 0–20 cm, 20–40 cm, and 40–60 cm, where TDR probes were located. Statistical indicators (*nRMSE*, *IA*, and *PBIAS*) suggest that HYDRUS 2D/3D is reliable in simulating field hydro-saline dynamics for irrigated carrots. The results obtained for the two crop seasons exhibit a strong correlation between the simulated and measured values for both soil water contents and electrical conductivities. The study also shows that HYDRUS 2D/3D allows more accurate simulations of soil water dynamics than soil salinity under these conditions. Overall, these results provide valuable insights for understanding the hydrological processes in arid regions and can help in improving the management of water resources in these areas.

Keywords: carrot; arid regions; irrigation methods; soil water and salt dynamics; HYDRUS 2D/3D

1. Introduction

Irrigation water management in Mediterranean regions faces significant challenges driven by the growing uncertainties associated with climate change. Increased irrigation usage is expected to significantly reduce the availability of fresh water with a potential decrease of 2–15% for each 2 °C of warming [1]. In Southern Tunisia, irrigated areas are a vital part of agricultural production but are constrained by the region's arid climate and limited water resources. According to [2,3], Southern Tunisia comprises approximately 14.4% of the nation's irrigated land, with irrigation primarily dependent on groundwater because of scarce surface water resources. The Médenine governorate experiences an arid climate, characterized by high evapotranspiration and low precipitation. The irrigated land in this governorate covers 4437 hectares, representing 1.18% of the total agricultural area [4]. Unfortunately, the exploitation of groundwater resources hit 13.52 Mm³ year⁻¹ in

Academic Editor: Claude Hammecker

Received: 10 December 2025

Revised: 16 January 2026

Accepted: 19 January 2026

Published: 21 January 2026

Copyright: © 2026 by the author. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

2013, reflecting an over-exploitation rate of 107%. Consequently, the water salinity levels soared to 10 g L^{-1} , and abandoned wells accounted for 46% of all the wells in the governorate [5]. Additionally, using saline irrigation water for sensitive and tolerant crops, particularly vegetables, worsens soil salinization. Indeed, prolonged irrigation with saline water can lead to salt accumulation in the root zone, impairing plant growth and threatening the long-term sustainability of agricultural systems [6–9].

In the face of these challenges, it is essential to adopt sustainable irrigation management practices that optimize water use while minimizing the negative impacts of salinity. Understanding water and salt distribution in the root zone and predicting future degradation requires specific monitoring actions, which can help to create a guideline for irrigation salinity management [10]. Evaluation of the crops' response to different salinity conditions needs time and experimental efforts, as it is influenced by the plant species, the level of salinity, and the environmental conditions. Numerical simulation models can be considered an economic and simple tool to better understand the salt dynamics with the aim of optimizing water use under arid conditions. Among models for simulating water flow, solute transport, and root water uptake in soils, HYDRUS [11] has been widely used in arid and semi-arid regions, offering a cost-effective and scientifically sound method for predicting salinization processes under various irrigation scenarios [12,13]. This model enables the development of strategic decisions for efficient irrigation management, reducing the risk of soil degradation and ensuring long-term agricultural productivity [14]. The capabilities of HYDRUS in evaluating, summarizing, and extrapolating information on water flow and solute transport processes in the vadose zone have been demonstrated in hundreds of scientific papers. Šimůnek et al. [15] reviewed several studies in which HYDRUS was applied to irrigated systems, mainly furrow and drip irrigation applications. More recently, [15] further expanded this earlier review to assess the current modeling capabilities of HYDRUS for a broader range of irrigation methods and related processes.

In the HYDRUS model, water flow and solute transport are modeled using a physically based numerical framework that requires accurate determination of soil hydraulic and transport parameters, which involve costly and laborious investigations [16]. Furthermore, as highlighted by [15], an intrinsic degree of uncertainty is associated with many of these parameters due to natural soil variability. To overcome this drawback, pedotransfer functions [17–20] can be used with the awareness that model parameters can be severely misestimated, thus invalidating the simulation results. A frequently applied option to effectively address the parameter uncertainties and enhance the predictive reliability of the model consists of using field observations to calibrate the model hydro-saline parameters, starting from guess values that are gathered from PTFs or measured on a limited number of samples with simple and routine laboratory/field techniques. The reliability of the calibrated parameters is then assessed by validating the model results with independent data. A brief summary of the theory underlying the HYDRUS model, the input parameters required for code execution, and the guidelines to obtain these parameters through model calibration and validation can be found in [21].

However, field-based multi-season evaluations that simultaneously assess coupled water-salt dynamics while comparing drip and surface irrigation under saline groundwater irrigation in arid environments remain limited. This study aims to investigate the capability of the HYDRUS 2D/3D model in simulating the soil water and solute dynamics under drip (DI) and surface irrigation (SI) in the arid conditions of Southern Tunisia. The comparison between these two irrigation methods is particularly relevant because agriculture in Southern Tunisia is progressively shifting from the traditional surface irrigation systems, where water is delivered by canal networks, to more modern pressurized systems that can improve water use efficiency and reduce water

consumption. In this context, the availability of a reliable prediction tool is crucial for designing sustainable irrigation management strategies, especially when moderately saline groundwater represents the main or only available irrigation resource. To address the practical limitations often encountered in data-scarce arid environments, this study proposes a calibration procedure that combines information obtained from laboratory measurements with a manual trial-and-error procedure to adjust the values of the saturated soil hydraulic conductivity to minimize the discrepancies between the simulated and measured soil water contents. The calibrated model is then applied for validation to a second irrigation season under SI and DI.

2. Materials and Methods

2.1. Field Description and Measurements

The field experiments were conducted over two consecutive fall–winter seasons (2017–2018 and 2018–2019) at the Agricultural Training Center of ELfjé, Médenine in Tunisia (33.456° N, 10.638° E). This region, situated in the arid southeastern part of Tunisia, is characterized by an arid climate with high annual potential evapotranspiration and scanty annual rainfall (average < 150 mm year⁻¹). During the two study seasons, total rainfall amounted to 234 mm in 2017–2018 and 176 mm in 2018–2019 (recorded from a weather station located close to the field experiment). The soil texture, as determined by the pipette method [22], is relatively uniform along the 0–60 cm profile and is classified as sandy according to the USDA soil classification system. Soil bulk density was determined on replicated undisturbed cores (8 cm diameter by 5 cm height) (Table 1).

Table 1. Physical properties of the soil profile.

Depth [cm]	0–20	20–40	40–60	Average
USDA Soil Classification	sandy	sandy	sandy	sandy
sand [%]	85.8	81.5	74.5	80.6
silt [%]	3.2	5.3	10.5	6.3
clay [%]	11.0	13.2	15.0	13.1
Soil dry bulk density [g cm ⁻³]	1.48	1.46	1.43	1.46

Over two consecutive fall–winter seasons, native variety carrots of the region were cultivated, with sowing taking place each year on 20 October. The crop cycle lasted approximately 140 days, and harvest took place on 3 March (2017–2018) and 12 March (2018–2019). The experimental field was divided into two theses based on irrigation method: surface (SI) and drip (DI) irrigation. For both theses, three replicate elementary plots were considered (Figure 1).

For the DI, the dimensions of the elementary plot were 2.5 m large and 25 m long. The irrigation system consisted of six drip lines installed with a spacing of 50 cm and positioned on the soil surface next to the carrot rows. Along the rows, carrots were seeded densely, with an average plant spacing of about 5 cm. The drippers, which were coextruded with the lateral, were spaced 40 cm along the line and operated at a nominal flow rate of 4 L h⁻¹. The SI thesis consisted of three 2 m × 2 m elementary plots delimited by shallow soil embankments and separated from each other by service paths. Carrots were seeded uniformly into each plot. The same experimental area and design were used for the two crop seasons.

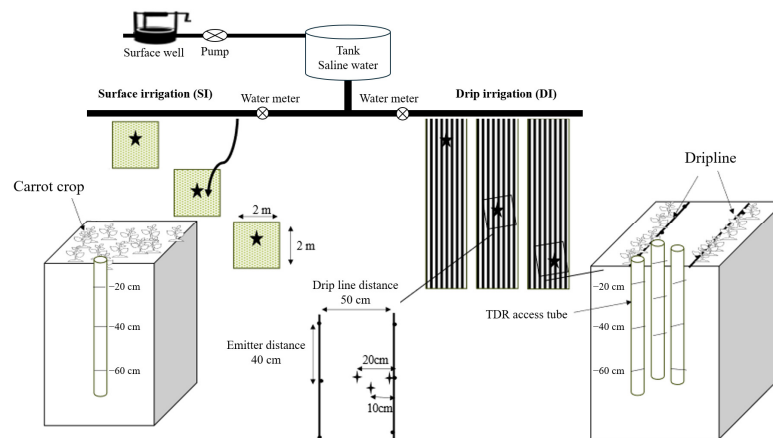


Figure 1. Layout of the experimental field.

Surface well water having a mean electrical conductivity (EC) of 7.4 dS m^{-1} was used for both seasons and irrigation systems. The water amounts delivered to the irrigation plots were measured using water meters. Irrigation scheduling was computed using the soil water balance method according to FAO Irrigation and Drainage Paper No. 56, with daily evapotranspiration (ET_0) estimated according to the Penman–Monteith equation [23]. The crop evapotranspiration under standard conditions (ET_m) was computed as

$$ET_m = ET_0 K_c \quad (1)$$

where K_c is a crop coefficient accounting for crop type and crop development stage.

Two approaches were considered for calculating ET_m : (i) the single crop coefficient method for surface irrigation, given that the canopy uniformly covered the soil surface at full stage development, and (ii) the dual crop coefficient method for drip irrigation, as the carrot rows were 50 cm spaced. In the dual-coefficient approach, K_c was calculated as

$$K_c = K_{cb} + K_e \quad (2)$$

where K_{cb} is the basal crop coefficient (transpiration component), and K_e is the soil water evaporation coefficient. Transpiration (T_m) and evaporation (E_m) under standard conditions were calculated as follows:

$$T_m = K_{cb} ET_0 \quad (3)$$

$$E_m = K_e ET_0 \quad (4)$$

The stage-dependent values of K_c and K_{cb} suggested by FAO-56 (initial, crop development, mid-season, and late season stages) were considered. A maximum allowed depletion of 35% was used to estimate irrigation amount and timing, following a soil water depletion threshold approach commonly adopted in irrigation scheduling studies [24]. Seasonal irrigation depths were 283 mm (applied in 12 irrigation events) in 2017–2018 and 176 mm (12 irrigations) in 2018–2019 for DI, and 294 mm (13 irrigations) in 2017–2018 and 378 mm (15 irrigations) in 2018–2019 for SI (Figure 2).

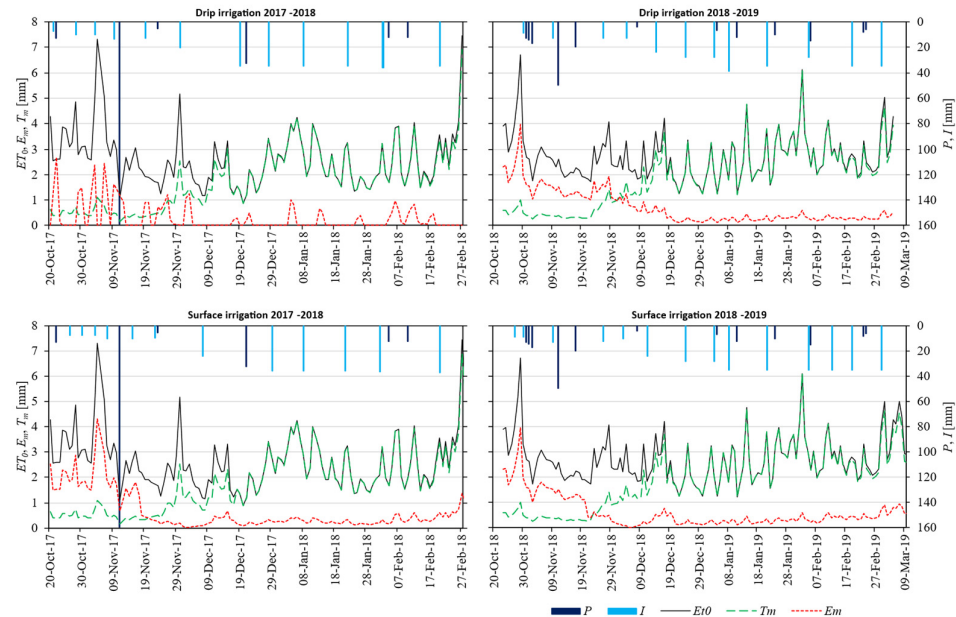


Figure 2. Reference evapotranspiration (ET_0), transpiration (T_m), and evaporation (E_m) under standard conditions for crop seasons 2017–2018 and 2018–2019, and both irrigation methods. Rainfall (P) and irrigation amount (I) data are also shown.

Soil volumetric water content and salinity were measured using tube access probes (Handheld Device HD2 IMKO Micromodultechnik, GmbH –Ettlingen, Germany) based on time-domain reflectometry (TDR). Access tubes were installed in each sub-plot, perpendicular to the dripline, at distances of 0, 10, and 20 cm from the emitter for the DI system and at the center of each plot for the SI system. Measurements were collected at three depth intervals (0–20, 20–40, and 40–60 cm) throughout the growing season. Monitoring was performed manually (event-based) using the handheld unit, with measurements collected before and after each irrigation event and after significant rainfall events.

The manufacturer's calibration curve of the TDR probe was checked for the experimental soil using two pots (30 cm width $\times$ 25 cm length). One pot was irrigated with the same saline water used for irrigation ($EC = 7.34 \text{ dS m}^{-1}$), while the other pot was irrigated with fresh water ($EC = 2.1 \text{ dS m}^{-1}$). Soil samples were collected using an auger to measure the gravimetric soil water content after oven drying the sample for 24 h at 105 °C. Gravimetric water content values were converted into volumetric water content, θ ($\text{cm}^3 \text{ cm}^{-3}$), using the bulk density of the pot. The same samples were used to measure the electrical conductivity of saturated paste extract, EC_e [dS m^{-1}], [25]. The relationship between θ values determined by TDR and the thermogravimetric method did not differ from the identity line ($R^2 = 0.9621$). The linear relationship between bulk soil electrical conductivity measured by TDR, EC_{TDR} , and the corresponding soil EC_e was $EC_e = 2.33 EC_{TDR}$ ($R^2 = 0.7595$).

2.2. HYDRUS 2D/3D Parametrization and Input

2.2.1. Governing Equations HYDRUS 2D/3D

HYDRUS 2D/3D v5.04 was used to simulate water and salt dynamics, including actual crop transpiration. The soil water distribution and redistribution processes are described with Richards' equation for variable-saturated flow, which incorporates a sink term (S) to account for root water uptake:

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x_i} \left[K \left(\frac{\partial h}{\partial x_j} + 1 \right) \right] - S \quad (5)$$

where θ is the volumetric water content [$L^3 L^{-3}$], h is the pressure head [L], S is a sink term expressing the rate of root water uptake [T^{-1}], x_i ($i = 1, 2, 3$) are the spatial coordinates [L], t is time [T], and K is the unsaturated hydraulic conductivity [$L T^{-1}$] given by

$$K(h, x, y, z) = K_s(x, y, z) K_r(h, x, y, z) \quad (6)$$

where K_r is the relative hydraulic conductivity and K_s the saturated hydraulic conductivity [LT^{-1}]. In HYDRUS 2D/3D, Equation (5) is solved numerically using the Galerkin finite element method, which is the default solver setting implemented in the code. Similarly, the non-reactive soil solute transport in the soil profile is simulated using the Fickian-based advection–dispersion equation, also solved using the Galerkin finite element method:

$$\frac{\partial \theta c}{\partial t} = \frac{\partial}{\partial x_i} \left(\theta D_{ij} \frac{\partial c}{\partial x_j} \right) - \frac{\partial q_i c}{\partial x_i} - S c_r \quad (7)$$

where c is the solute concentration in liquid phase [$M L^{-3}$], x_i and x_j ($i, j = 1, 2, 3$) are the spatial coordinates [L], q_i ($i = 1, 2, 3$) are the volumetric water flux density in three directions [$L T^{-1}$], D_{ij} is the hydrodynamic dispersion coefficient tensor [$L^2 T^{-1}$], and c_r [$M L^{-3}$] is the sink term concentration to account for root solute uptake.

The sink term, S , in Equation (5) is evaluated as a function of the maximum uptake rate, S_m , and a dimensionless water stress response function, $\alpha(h)$:

$$S(h) = \alpha(h) S_m \quad (8)$$

The function $\alpha(h)$ assumes values between 0 and 1 and was expressed by the linear model proposed by [26]. The maximum uptake rate S_m can be estimated from the crop transpiration under standard condition, T_m , and a non-uniform normalized water uptake distribution function $b(x, y, z)$:

$$S_m = b(x, y, z) A_t T_m \quad (9)$$

in which A_t is the area of the soil surface associated with the transpiration process. The model proposed by [27] is implemented in HYDRUS 2D/3D to describe the normalized water uptake distribution function, which accounts for non-uniform water application (e.g., drip irrigation) and root length density.

2.2.2. Domain Flow, Boundary Conditions, and Initial Conditions

Water and solute distributions were analyzed using two different boundary condition configurations for the drip and surface irrigation methods, respectively. Simulations were separately conducted for the two irrigation systems and the two growing seasons of carrot crops (2017–2018 and 2018–2019).

For the DI method, a two-dimensional plane simulation domain of 100 cm depth and 25 cm width was considered in which the domain width corresponds to half of the spacing between two adjacent drip laterals (i.e., symmetry condition). This approach is consistent with previous HYDRUS-2D applications for drip irrigation, where the computational domain is selected sufficiently large to minimize lateral boundary effects on the simulated wetting pattern [28]. The domain was discretized with 826 nodes, corresponding to 1538 general elements. The finite-element mesh was generated in HYDRUS using the unstructured triangular mesh generator (MeshGen), and the final number of nodes/elements resulted from the selected targeted element size and the applied local refinements. Mesh refinement was carried out near the soil surface and near the wetted

strip where the flux changes rapidly. The simulations were partitioned into irrigation runs and redistribution runs. During the irrigation runs, the simulation time length equaled the duration of the irrigation event, and the top boundary conditions were imposed as a constant-flux over the wetted area and atmospheric over the remaining surface. In all the simulations, the wetting bulb remained far from the boundaries of the flow domain (Figure 3).

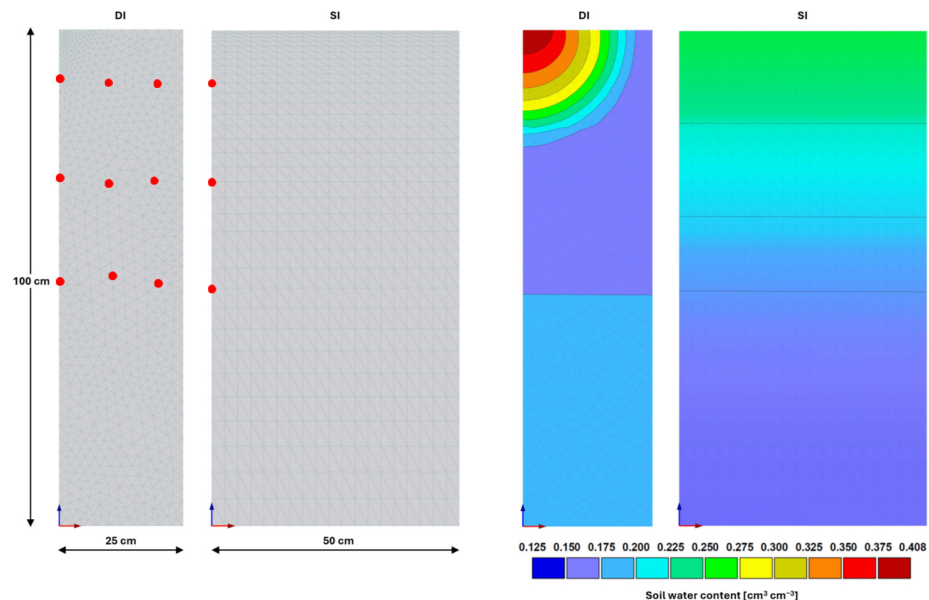


Figure 3. Finite-element meshes and locations of the observation nodes adopted (**left** panels) and simulated spatial distributions of volumetric soil water content (**right** panels) for drip irrigation (DI) and surface irrigation (SI) at the end of the irrigation event on 8 January 2019.

The emitter flux density was computed considering the dripline as a uniform line source [12] by dividing the emitter flow discharge by the wetted area that was assumed as a 5 cm wide strip along the dripline with a length equal to the emitter spacing (e.g., $5 \times 40 = 200 \text{ cm}^2$). For the 2017–2018 season, the emitter nominal flow of 4 L h^{-1} was considered; thus, the imposed boundary flux density was 20 cm h^{-1} . The actual dripper flow rate was considered for each irrigation during the 2018–2019 season, which, due to different operating pressure conditions, resulted in a flux density ranging from 9 to 13 cm h^{-1} . The redistribution runs covered the periods between two consecutive irrigations. In this case, the entire top boundary was set as atmospheric conditions.

The initial water content for the first run was prescribed as spatially uniform at $0.21 \text{ cm}^3 \text{ cm}^{-3}$, corresponding to field capacity. For each subsequent run, the spatial distribution of water content at the end of the preceding simulation was used as the initial condition. Rooting depths were updated across runs to reflect root development measured over the growing season. Then, a total of 25 simulations were performed in the 2017–2018 season and 32 in the 2018–2019 season.

Despite water flow under surface irrigation (SI) is essentially one-dimensional, HYDRUS 2D/3D simulations were conducted with a 50 cm width by 100 cm depth flow domain representing a cross-section under uniformly distributed surface irrigation. The domain was discretized into 680 nodes corresponding to 1254 triangular elements according to a regular mesh. Near-surface refinement was considered to better resolve the infiltration front and the associated gradients (Figure 3). The top boundary condition was set to atmospheric, and the irrigation flux was considered as rainfall. For this irrigation

method, 11 consecutive simulations were performed for both crop seasons to account for the evolution of the root system during the carrot growing period.

For both DI and SI, the third type of concentration flux was considered as the surface boundary condition for solute transport. The solutes were assumed to be non-reactive, and solubilization or dissolution processes were neglected. The measured electrical conductivity of irrigation water was considered as a time-dependent boundary condition, taking into account that solute input occurred only during irrigation. A no-flux boundary condition was set at the lateral edges of the domain, and a free drainage boundary condition was applied at the bottom because the groundwater depth is approximately 50 m; thus, capillary rise is negligible. The initial soil bulk electrical conductivity was assumed to vary linearly along the soil profile between 10.7 dS m⁻¹ and 9.3 dS m⁻¹ in the 2017/2018 season, and between 8.96 and 6.45 dS m⁻¹ in the 2018/2019 season. These values were determined based on a field survey of the saturated paste extracts collected immediately before irrigation.

2.2.3. Soil Hydraulic Parameters and Solute Transport Parameters

The execution of the HYDRUS 2D/3D code requires the specification of the soil water retention curve (SWRC) and hydraulic conductivity function parameters. The SWRC was determined in the laboratory using a hanging water column apparatus [29] for the wet range of the curve ($-5 < h \leq -100$ cm) and a pressure plate apparatus [30] for the dry range ($-100 < h \leq -15,000$ cm). Two replicated undisturbed soil samples, 8 cm in diameter by 5 cm in height, were collected from three layers at the experimental site: 0–20, 20–40, and 40–60 cm. The water retention data were fitted using RETC software to determine the van Genuchten model parameters [31] for each layer (Table 2). The saturated soil hydraulic conductivity, K_s , was measured both in the laboratory using the constant head method [30] and the ICW permeameters (Soil moisture equipment corp., Goleta, CA, USA, 2008) and in the field by the double ring infiltrometer method [32] (Table 2).

Modeling solute transport and salinity dynamics requires longitudinal, ε_L , and transversal, ε_T , dispersivities, whereas molecular diffusion and the adsorption isotherm coefficient are neglected. Gelhar et al. [33] compiled a large dataset of longitudinal dispersivity from field studies. They observed that dispersivity generally rises with the scale of measurement, with typical values ranging from less than one meter to several hundred meters. This observation aligns with empirical studies by [34,35], who noted that longitudinal dispersivity is typically one-tenth of the transport scale. For 2D flow simulations, estimating transverse dispersivity $\varepsilon_T = 0.1\varepsilon_L$ is a common simplification, and HYDRUS 2D/3D automatically adjusts the dispersion coefficient [36] (Table 2).

Table 2. Soil hydraulics and solute transport parameters.

Soil Depth [cm]	θ_s [cm ³ cm ⁻³]	θ_r [cm ³ cm ⁻³]	α [cm ⁻¹]	n [-]	K_{s-1} [cm d ⁻¹]	K_{s-2} [cm d ⁻¹]	K_{s-3} [cm d ⁻¹]	ε_L [cm]	ε_T [cm]
0–20	0.412	0.042	0.013	2.193	107.26	203.49	-	25	2.5
20–40	0.390	0.040	0.013	2.193	98.43	266.92	367.2	25	2.5
40–60	0.370	0.042	0.013	2.193	29.53	277.33	379.2	25	2.5
average	0.391	0.041	0.013	2.193	78.41	249.25	373.2	25	2.5

θ_r : residual water content; θ_s : saturated water content; α : SWRC scale parameter; n : SWRC shape parameter; K_{s-1} : saturated hydraulic conductivity (ICW permeameter); K_{s-2} : saturated hydraulic conductivity (constant head permeameter); K_{s-3} : saturated hydraulic conductivity (double ring infiltrometer); ε_L : longitudinal dispersivity; ε_T : transversal dispersivity.

2.2.4. Calibration and Validation Process

The soil water content measurements were used to evaluate model performance. In particular, the soil water content (θ) values estimated by the model at the observation points were compared with the measured values. At this aim, observation nodes were placed within the flow domain at locations corresponding to the field measurements. The 2018–2019 season data were used to calibrate the model, followed by a trial-and-error procedure to select the saturated hydraulic conductivity (K_s) that minimized deviations between the simulated and observed values at the three monitored depths (Table 2). The best fit was achieved with a unique K_s value of 78.41 cm d⁻¹. The measured soil water content data for the 2017–2018 season and the electrical conductivity data for both seasons were used for validating HYDRUS 2D/3D.

The model results were assessed using different statistical indices: the normalized root mean square error ($nRMSE$), the index of agreement (IA), and the percentage bias ($PBIAS$). These indices were defined as follows:

$$nRMSE = \sqrt{\frac{\sum_{i=1}^n (O_i - P_i)^2}{n \bar{O}}} \quad (10)$$

in which O_i and P_i are the observed and estimated values of the volumetric water content or bulk soil electrical conductivity, and $\bar{O}$ represents the average of the observed values. $nRMSE$ is an index of the “predictive power” of a fitted model, where $nRMSE = 0$ indicates perfect prediction (i.e., no discrepancies between the predicted and measured values).

The index of agreement specifies the degree to which the observed deviations from $\bar{O}$ correspond, both in magnitude and sign, to the predicted deviations from $\bar{O}$ [37] and is given by

$$IA = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} \quad 0 \leq IA \leq 1 \quad (11)$$

A computed value of the index of agreement of 1 indicates perfect agreement between the measured and predicted values, while 0 indicates no agreement at all.

The percentage bias ($PBIAS$) measures the average tendency of the estimated values to be larger or smaller than their observed ones. This index is defined as

$$PBIAS = \frac{\sum_{i=1}^n (O_i - P_i)}{\sum_{i=1}^n O_i} \cdot 100 \quad (12)$$

Positive values of $PBIAS$ indicate an underestimation, while negative values indicate an overestimation of the estimated values [38].

3. Results and Discussion

3.1. Simulation of Soil Water Content

The seasonal daily dynamics of the measured and estimated soil water content, at the three considered depths (0–20, 20–40, and 40–60 cm), are shown in Figure 4 for the calibration year and Figure 5 for the validation year. For the DI method, each measured value is the average of the three θ data collected at a given depth and a distance of: 0, 10, and 20 cm from the emitter.

For both methods, the measured θ values increased quickly after irrigation or effective rainfall events, and then gradually decreased until the next irrigation due to redistribution. Water content variations were more noticeable near the soil surface, as commonly found in the literature (e.g., [39]). The deep layers (20–40 and 40–60 cm) displayed smaller and smoother water contents, and this behavior was more evident for drip than surface irrigation. Tlig et al. [40] found that the fluctuations of θ were higher in

the drip than the surface method and concluded that drip irrigation is more effective in maintaining a higher water content in the upper soil layer compared to surface irrigation. The results of this study partially confirm these findings, as variation in the measured water content values tended to be more pronounced on the surface layer for the DI than the SI method, whereas the latter method yielded generally higher θ values in the subsurface 20–40 cm layer as a consequence of a more rapid infiltration into the deep layers.

The simulated water contents after the calibration procedure closely matched the measured θ values at the surface layer (0–20 cm) and, even if with a more pronounced dynamic, also at the deeper layers (Figure 4). At each depth, the simulated water contents for the DI method achieved higher water contents than the SI one, thus confirming that localized water infiltration allows for better soil water storage, resulting in higher soil water content. The observed differences between the peaks in the measured and simulated water content at the upper layer of the drip-irrigated system are due to the delay in TDR measurements that were generally conducted from 1 to 4 h after the end of irrigation.

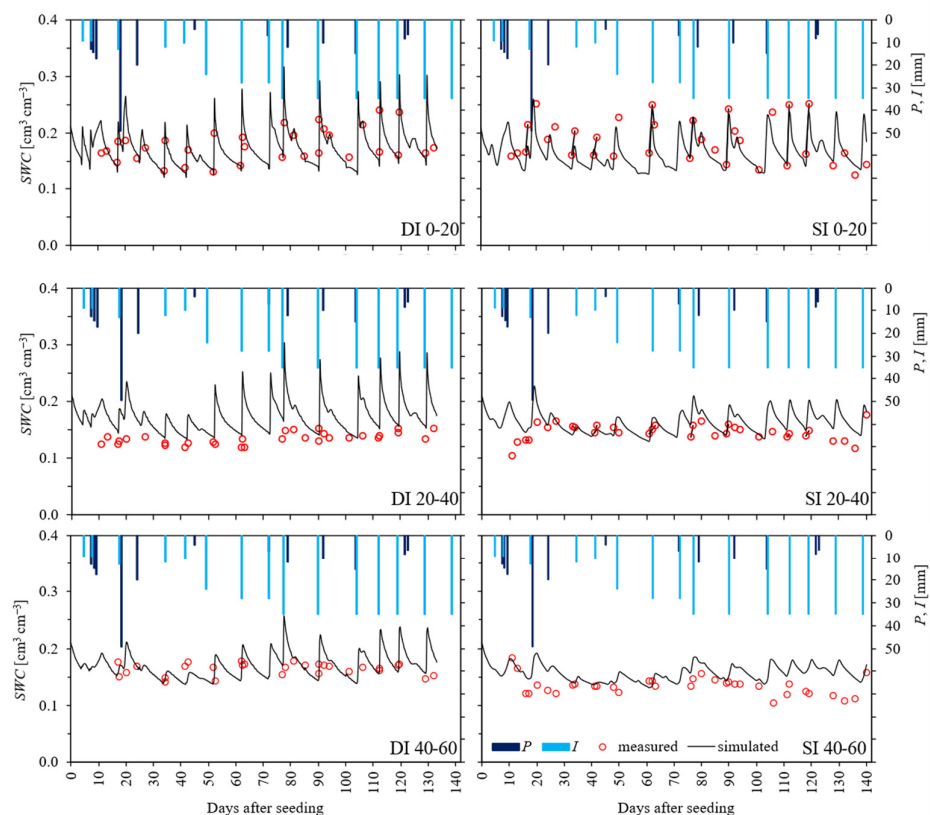


Figure 4. Comparison between the simulated and measured soil water contents (SWC) at different depths under drip irrigation (DI) and surface irrigation (SI) for the calibration season 2018–2019. Precipitations P and irrigations I are also indicated.

The statistics of HYDRUS 2D/3D performance, i.e., $nRMSE$, IA , and $PBIAS$ values, are reported in Table 3 for both plots (DI and SI) and crop seasons (calibration 2018–2019 and validation 2017–2018). For the calibration season (2018–2019), surface irrigation simulation provided more accurate results than the drip one, especially for the upper soil layers (0–20 cm) with an $nRMSE$ of 0.150 for the former irrigation method compared to

0.203 for the latter (Table 3). Less accurate predictions were observed for the subsurface layers ($nRMSE = 0.188$ – 0.325 for DI compared to 0.200 – 0.235 for SI). Comparison with widely accepted reference values for these indicators showed an acceptable performance of HYDRUS 2D/3D simulations, but deep soil layers were generally more susceptible to biases in both DI and SI methods, as shown by the lower values of IA and higher absolute values of $PBIAS$. With the exception of the 0–20 cm layer for surface irrigation, the simulated soil water contents always overestimated the measured ones, as shown by the negative values of $PBIAS$ (Table 3).

For the validation season (2017–2018), the model performance was similar and even better than calibration (Table 3). In the context of drip irrigation, slightly larger differences between the simulated and measured values were observed only at the deepest layer (40–60 cm). For the two surface layers, predictions improved as detected by lower $nRMSE$ values ($nRMSE = 0.145$ for the 0–20 cm layer and 0.173 for the 20–40 cm layer), higher IA values ($IA = 0.775$ and 0.426 , respectively), and lower absolute values of $PBIAS$. A trend to overestimate θ was also confirmed for the validation season for the upper and intermediate layers.

Existing applications of HYDRUS to drip-irrigated crops yielded accuracy levels comparable to those of our study. Ghazouani et al. [12] reported $RMSE$ values lower than $0.04 \text{ cm}^3 \text{ cm}^{-3}$ for eggplants grown under semi-arid conditions. Wang et al. [41] found $RMSE$ values of 0.03 – $0.05 \text{ cm}^3 \text{ cm}^{-3}$ for drip-irrigated maize in a subhumid region. Considering the mean values of the measured water contents at the three depths and two crop seasons, the $RMSE$ values ranged from 0.026 to $0.041 \text{ cm}^3 \text{ cm}^{-3}$, which is in line with values found in the literature. Our results are slightly worse than those obtained by [42], who report a maximum value of $nRMSE = 0.115$ for maize under drip irrigation.

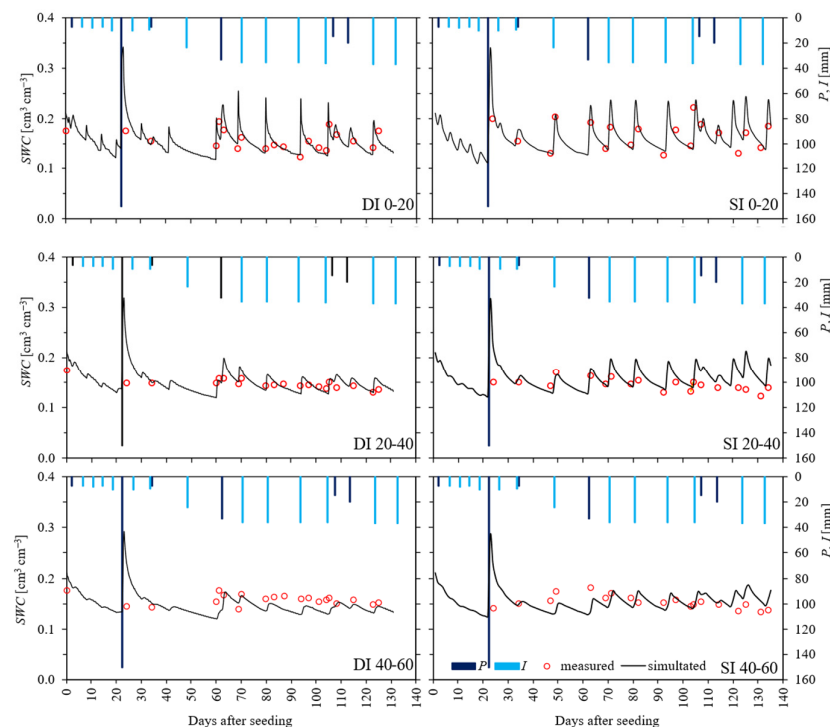


Figure 5. Comparison between the simulated and measured soil water content (SWC) at different depths under drip irrigation (DI) and surface irrigation (SI) for the validation season 2017–2018. Precipitations (P) and irrigations (I) are also indicated.

In the context of surface irrigation, the improved performance of validation compared to calibration was confirmed for the 0–20 cm layer in which $nRMSE$ reduced from 0.150 to 0.089, IA increased from 0.836 to 0.919, and $PBIAS$ decreased from 0.246 to −0.045. For deeper layers (20–40 cm and 40–60 cm), differences between the calibration and the validation datasets were less pronounced and not always in the same direction. In particular, the accuracy increased, as indicated by decreasing $nRMSE$ values in both layers (Table 3), but agreement worsened, as indicated by decreased IA values. The water content was always underestimated, and for the intermediate layer, the average underestimation increased from the calibration to the validation seasons. The opposite result was found for the deepest layer (40–60 cm).

This result contrasts with [43], who found that the largest error occurs in the surface layer, where soil variability and flux variations are difficult to represent under furrow irrigation. According to [44], HYDRUS-2D could adequately simulate the temporal and spatial distribution of soil water content for conventional furrow irrigation with R^2 values between measured and simulated θ values that ranged between 0.721 and 0.795. Hu et al. [39] reported good agreement between simulated and measured θ values with $RMSE$ values for flood irrigation that ranged between 0.011 and 0.095 $\text{cm}^3 \text{cm}^{-3}$. Ranjbar et al. [45] also found that HYDRUS-2D accurately simulated θ in different depths under the furrows and ridges with $nRMSE = 0.792$ and $R^2 = 0.783$ for the validation season.

Table 3. Statistical indices of estimated vs. measured soil water content values at different depths and irrigation methods for calibration and validation crop seasons.

Irrigation Method	Depth	Calibration (2018–2019)			Validation (2017–2018)		
		$nRMSE$	IA	$PBIAS$	$nRMSE$	IA	$PBIAS$
Drip irrigation	0–20	0.203	0.747	−0.138	0.145	0.775	−0.081
	20–40	0.325	0.315	−1.139	0.173	0.426	−0.281
	40–60	0.188	0.281	−0.232	0.195	0.179	0.346
Surface irrigation	0–20	0.150	0.836	0.246	0.089	0.919	−0.045
	20–40	0.200	0.453	−0.392	0.197	0.412	−0.729
	40–60	0.235	0.451	−0.540	0.161	0.208	−0.219

3.2. Simulation of Soil Salinity

Comparison between the simulated and measured values of soil bulk electrical conductivity EC_s at different depths (0–20, 20–40, and 40–60 cm) is shown for drip and surface irrigation and the two irrigation seasons in Figures 6 and 7.

For both crop seasons, the measured EC_s drastically increased following irrigation, and decreased after rainfall events. The decrease is particularly evident following rainfall events of 159 mm in the 2017–2018 season and 49 mm in the 2018–2019 one, which may have moved the salts beyond the monitored soil depth. During the 2018–2019 season, soil bulk electrical conductivity values measured in the surface irrigation plot were higher than the corresponding ones in drip irrigation, probably because the lower rainfall amount (49 mm) was less effective in leaching the salts down in the soil profile. Conversely, the larger rainfall event (159 mm) occurring in the 2017–2018 season contributed to homogenizing the salinity between the two irrigation systems.

For a study conducted in the same climatic environment of the southeast of Tunisia, [46] noted that the ability of fall–winter rainfall to leach salts varies and it is influenced by both the total amount of rainfall and the distribution of the rainfall events.

For both seasons, the EC_s in the surface layer of the DI plot were slightly higher than at the deep layer. The higher soil salinity can be attributed to the reduced leaching as suggested by [47]. These authors also found that more frequent application of smaller

water volumes, which is typical in drip systems, prevents salt build-up near the soil surface, but this does not always prevent accumulation at deeper depths, depending on drainage characteristics and the water table depth.

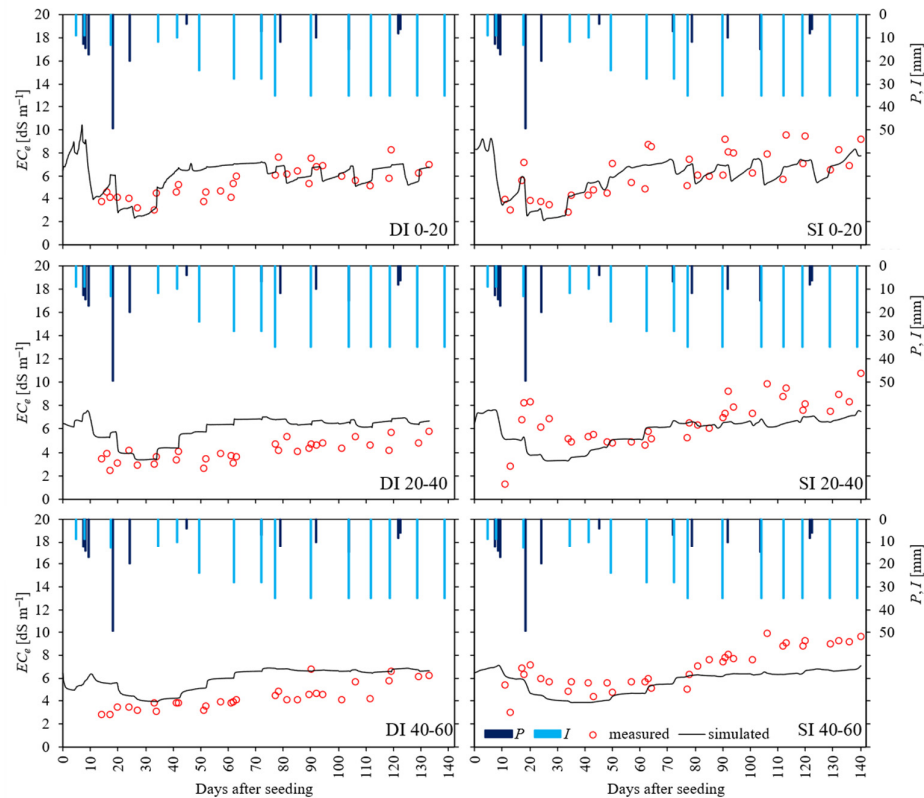


Figure 6. Comparison between the simulated and measured soil electrical conductivity (EC_s) at different depths under drip irrigation (DI) and surface irrigation (SI) for the calibration season 2018–2019. Precipitations (P) and irrigation (I) are also indicated.

HYDRUS 2D/3D fairly simulated the salt dynamics in the soil profile, especially the leaching of salt after rainfall events (Figures 6 and 7). Statistics for the model performance listed in Table 4 show that the simulations performed better at the surface layer with $nRMSE$ values ranging from 0.161 to 0.293 and IA values between 0.685 and 0.850 depending on the irrigation method and the crop season. For a given irrigation method and crop season, the EC_s predictions always worsened with depth, thus showing that the model calibration performed on the basis of the measured soil water content was not completely efficient in estimating soil salinity evolution for subsurface layers. In the deep layers (20–40 and 40–60 cm), soil salinity was systematically underestimated or overestimated depending on season and irrigation method (Figures 6 and 7), and the $PBIAS$ absolute values were from 4 to 90 times higher than the $PBIAS$ value of the surface layer. It was concluded that although HYDRUS 2D/3D can simulate salt dynamics with a relatively high precision at the surface layer, the more complex flow regimes in deeper soil layers present challenges where heterogeneities and preferential flow paths become significant for soil salinity predictions.

Simunek et al. [11], in their comprehensive review of HYDRUS applications, acknowledged that while the model is capable of simulating salinity in various irrigation systems, its performance can vary based on the type of soil, boundary conditions, and

initial moisture levels. In particular, leaching efficiency and deep percolation processes may play critical roles in salinity simulation. In cases where irrigation water does not adequately leach salts from deeper layers, the model may over- or underestimate salinity accumulation. Skaggs et al. [14] also noted that HYDRUS hardly predicts changes in salinity at depth due to the complexity of solute transport processes.

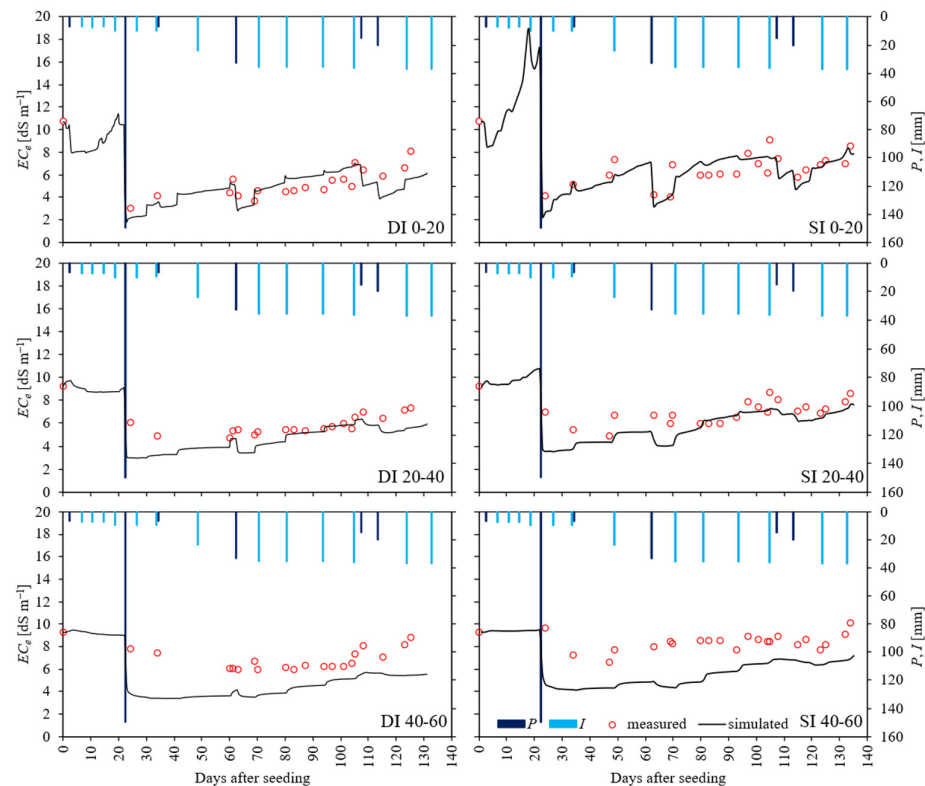


Figure 7. Comparison between simulated and measured soil electrical conductivity (EC_s) at different depths under drip irrigation (DI) and surface irrigation (SI) for 2017–2018 crop season. Precipitations (P) and irrigation (I) are also indicated.

Despite salinity predictions generally worsening with depth, it is worth noting that HYDRUS 2D/3D performances at each depth were generally better for surface than drip irrigation, as shown by lower $nRMSE$ values and higher IA values, with the only exception of the 40–60 cm layer in the 2017–2018 season. Also, the absolute values of $PBIAS$ were lower for SI in 5 out of 6 comparisons. Thus, our results show that HYDRUS 2D/3D simulates the salinity evolution with higher precision and accuracy under surface irrigation than under drip irrigation.

For drip irrigation, a certain variability in the measured and simulated EC_s values was observed in the study of [48], with an $RMSE$ value ranging from 0.22 to 0.55 $dS\ m^{-1}$, which corresponds to a range from 1.66 to 1.97 $dS\ m^{-1}$ with our data. One possible reason for the observed discrepancies between the measured and simulated EC_s values could be due to the spatial variability in EC_s measured surrounding different emitters, and to the gradient of salt concentration occurring in the soil. This interpretation is consistent with the findings of Baiamonte et al. [49], who showed that variability in soil hydraulic parameters around surface and subsurface emitters can markedly alter the geometry of the wetted bulb and, consequently, the spatial patterns of water and salt accumulation in

the root zone. Phogat et al. [50] reported that their model over-predicted the electrical conductivity of the extracted soil solution at a depth of 25 cm and under-predicted it at a depth of 100 cm in drip-irrigated mandarin orchards. The difference between the measured and simulated EC_e values was relatively larger at a depth of 50 cm, with a mean absolute error (MAE) of 0.47 dS m^{-1} , compared to the mean MAE of 0.19 dS m^{-1} at a depth of 25 cm.

For surface flood irrigation, [51] found that the 1D version of HYDRUS showed relatively good agreement between simulated and measured salt content data, with performances that increased with depth. For furrow irrigation, [52] observed increased salinity at deeper layers due to gravity-driven flow and preferential flow paths. Therefore, simulating surface irrigation can also be problematic due to non-uniform water and salt distribution.

Table 4. Statistical indices of estimated vs. measured soil electrical conductivity values at different depths and irrigation methods for calibration and validation crop seasons.

Irrigation Method	Depth	Calibration (2018–2019)			Validation (2017–2018)		
		<i>n</i> RMSE	IA	PBIAS	<i>n</i> RMSE	IA	PBIAS
Drip irrigation	0–20	0.293	0.690	−0.187	0.253	0.685	0.020
	20–40	0.554	0.415	−1.413	0.224	0.556	0.865
	40–60	0.528	0.445	−1.236	0.353	0.396	1.759
Surface irrigation	0–20	0.217	0.827	0.146	0.161	0.850	0.128
	20–40	0.302	0.594	0.426	0.188	0.647	0.551
	40–60	0.260	0.656	0.530	0.334	0.320	1.426

3.3. Implications for Irrigation Management

HYDRUS 2D/3D proved to be a useful process-based tool to interpret soil water and salinity dynamics under surface and drip irrigation that are difficult to derive only from measurements. In this context, HYDRUS can be used to support irrigation management by testing alternative irrigation doses and timings and evaluating their expected effects on soil moisture depletion and salinity build-up/leaching within the root-zone profile. However, HYDRUS is not suited to manage irrigation in the field (i.e., to predict when and how much to irrigate) given that it simulates the water and solute fluxes for a given irrigation schedule. Furthermore, the achievable precision of model-based irrigation recommendations depends on the quality of input data and on spatial variability in field conditions.

The modeling set-up should be implemented in the context of the observation scale and the adopted level of spatial representation. In this study, the soil water content and bulk electrical conductivity were measured at specific locations, whereas HYDRUS simulated spatially averaged conditions within a representative 2D domain. Therefore, part of the mismatch can be attributed to the different spatial scales and to inherent field heterogeneity. Moreover, the modeling geometry represents the dominant flow and transport processes, but it does not explicitly resolve sub-scale variability in hydraulic properties or localized preferential pathways, which can play a larger role at higher depths and under localized wetting patterns. Indeed, in this study, HYDRUS provided more robust results for soil water dynamics than for salinity and at the surface than at deep locations.

In the context of “precision irrigation” applications, the model has the potential to be a decision-support tool if used in combination with field monitoring (e.g., measurement of volumetric soil water content) that allows for periodic adjustment of irrigation scheduling and accounts for uncertainties.

4. Conclusions

This study evaluated the performance of the HYDRUS 2D/3D in simulating soil water flow and solute transport dynamics under drip and surface irrigation systems for carrot crops using moderately saline water in the arid conditions of Southern Tunisia. Model performance was evaluated against field measurements of soil water content and bulk soil electrical conductivity at 0–20, 20–40, and 40–60 cm during two growing seasons.

The HYDRUS 2D/3D model reproduced soil water content with acceptable accuracy across methods and depths, with $nRMSE$ values generally ranging from 0.089 to 0.325 and best performance in the upper 0–20 cm of the soil profile. The model accuracy declined with depth, likely as a consequence of heterogeneous soil hydraulic properties that activated non-uniform flow. Overall, these results support the use of HYDRUS 2D/3D to represent irrigation-driven wetting–drying cycles in the monitored root-zone profile.

In terms of soil salinity, the model successfully simulated the main seasonal behavior, including salt accumulation and leaching dynamics, especially after significant rainfall events of the two seasons. The agreement between observed and simulated salinity was stronger in surface layers, while deeper layers exhibited greater discrepancies, confirming that predicting salinity below the upper layer remains challenging. Across depths and seasons, salinity simulations were generally more accurate under SI than under DI. This indicates that the localized nature of DI associated with high spatial gradients around emitters amplifies the impact of soil hydraulic properties, small-scale variability, and salinity sensor location on simulated salt patterns. Therefore, irrigation methods should be explicitly considered when using process-based models to assess salinization risk.

Overall, the integration of field observations with HYDRUS 2D/3D simulations provided a field-based, multi-season evaluation of HYDRUS 2D/3D for coupled water–salt dynamics in an arid, saline-irrigated carrot system. The results also showed that the seasonal rainfall events are key drivers of salt leaching and can reduce differences between irrigation methods. Finally, this study delineates the reliability domain of the model, which is essential for managing irrigation (i.e., it proved robust for soil water dynamics and less skilled for salinity at higher depth and under localized irrigation). These findings support the use of HYDRUS 2D/3D as a possible decision-support tool for irrigation management in arid regions under saline-water conditions, enabling more sustainable use of water resources and reducing the risk of soil salinization. Future research should incorporate detailed root growth monitoring and consider spatial variability in soil properties to enhance model calibration and predictive accuracy.

Author Contributions: Conceptualization, K.N. and M.I.; data curation, W.T. and D.A.; formal analysis, W.T.; investigation, W.T. and F.E.M.; supervision, M.I. and D.A.; writing—original draft preparation, W.T., D.A. and M.I.; writing—review and editing, D.A., M.I. and K.N. All authors have read and agreed to the published version of the manuscript.

Funding: This study was funded by Università degli Studi di Palermo (FFR 2025).

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Cramer, W.; Guiot, J.; Fader, M.; Garrabou, J.; Gattuso, J.-P.; Iglesias, A.; Lange, M.A.; Lionello, P.; Llasat, M.C.; Paz, S.; et al. Climate Change and Interconnected Risks to Sustainable Development in the Mediterranean. *Nat. Clim. Change* **2018**, *8*, 972–980. <https://doi.org/10.1038/s41558-018-0299-2>.
2. Food and Agriculture Organization of the United Nations. *AQUASTAT Profil de Pays—Tunisie*; Food and Agriculture Organization: Rome, Italy, 2015.
3. Ministère de l’Agriculture, des Ressources Hydrauliques et de la Pêche. *Rapport National du Secteur de L’eau*; Ministère de l’Agriculture, des Ressources Hydrauliques et de la Pêche: Tunis, Tunisia, 2018.
4. Commissariat Régional au Développement Agricole (CRDA). *Arrondissement de Production Végétale*; Commissariat Régional au Développement Agricole: Médenine, Tunisia, 2017.
5. Commissariat Régional au Développement Agricole (CRDA). *Arrondissement Des Ressources En Eau*; Commissariat Régional au Développement Agricole: Médenine, Tunisia, 2013.
6. Rhoades, J.D.; Kandiah, A.; Mashali, A.M.; Rhoades, J.D. *The Use of Saline Waters for Crop Production*; FAO irrigation and drainage paper; Food and Agriculture Organization of the United Nations: Rome, Italy, 1992.
7. Nagaz, K.; Masmoudi, M.M.; Mechli, N.B. Impacts of Irrigation Regimes with Saline Water on Carrot Productivity and Soil Salinity. *J. Saudi Soc. Agric. Sci.* **2012**, *11*, 19–27. <https://doi.org/10.1016/j.jssas.2011.06.001>.
8. Dhouha, L.; Rajouene, M.; Hafedh, R.; Habib, A. 30 Years Saline Water Irrigation Effects on Soil Characteristics. *Int. J. Eng. Res. Technol.* **2014**, *2*, 5–13.
9. Kanzari, S.; Ben Nouna, B.; Ben Mariem, S.; Rezig, M. Hydrus-1D Model Calibration and Validation in Various Field Conditions for Simulating Water Flow and Salts Transport in a Semi-Arid Region of Tunisia. *Sustain. Environ. Res.* **2018**, *28*, 350–356. <https://doi.org/10.1016/j.serj.2018.10.001>.
10. Skaggs, T.H.; Suarez, D.L.; Goldberg, S. Effects of Soil Hydraulic and Transport Parameter Uncertainty on Predictions of Solute Transport in Large Lysimeters. *Vadose Zone J.* **2013**, *12*, vzj2012-0143. <https://doi.org/10.2136/vzj2012.0143>.
11. Šimůnek, J.; Van Genuchten, M.T.; Šejna, M. Development and Applications of the HYDRUS and STANMOD Software Packages and Related Codes. *Vadose Zone J.* **2008**, *7*, 587–600. <https://doi.org/10.2136/vzj2007.0077>.
12. Ghazouani, H.; Autovino, D.; Rallo, G.; Rallo, G.; Provenzano, G. Using HYDRUS-2D model to assess the optimal drip lateral depth for Eggplant crop in a sandy loam soil of central Tunisia. *Ital. J. Agrometeorol.* **2016**, *1079*, 47–58. <https://doi.org/10.19199/2016.1.2038-5625.047>.
13. Ghazouani, H.; Douh M’hamdi, B.; Autovino, D.; Bel Haj, A.M.; Rallo, G.; Provenzano, G.; Boujelben, A. Optimizing Subsurface Dripline Installation Depth with Hydrus 2D/3D to Improve Irrigation Water Use Efficiency in the Central Tunisia. *Int. J. Metrol. Qual. Eng.* **2015**, *6*, 402. <https://doi.org/10.1051/ijmqe/2015024>.
14. Skaggs, T.H.; Shouse, P.J.; Poss, J.A. Irrigating Forage Crops with Saline Waters: 2. Modeling Root Uptake and Drainage. *Vadose Zone J.* **2006**, *5*, 824–837. <https://doi.org/10.2136/vzj2005.0120>.
15. Lazarovitch, N.; Kisekka, I.; Oker, T.E.; Brunetti, G.; Wöhling, T.; Xianyu, L.; Yong, L.; Skaggs, T.H.; Furman, A.; Sasidharan, S.; et al. Chapter Two—Modeling of Irrigation and Related Processes with HYDRUS. In *Advances in Agronomy*; Sparks, D.L., Ed.; Academic Press: Cambridge, MA, USA, 2023; Volume 181, pp. 79–181.
16. Angelaki, A.; Bota, V.; Chalkidis, I. Estimation of Hydraulic Parameters from the Soil Water Characteristic Curve. *Sustainability* **2023**, *15*, 6714. <https://doi.org/10.3390/su15086714>.
17. Nemes, A.; Schaap, M.G.; Wösten, J.H.M. Functional Evaluation of Pedotransfer Functions Derived from Different Scales of Data Collection. *Soil Sci. Soc. Am. J.* **2003**, *67*, 1093–1102. <https://doi.org/10.2136/sssaj2003.1093>.
18. Castellini, M.; Iovino, M. Pedotransfer Functions for Estimating Soil Water Retention Curve of Sicilian Soils. *Arch. Agron. Soil Sci.* **2019**, *65*, 1401–1416. <https://doi.org/10.1080/03650340.2019.1566710>.
19. D’Emilio, A.; Aiello, R.; Consoli, S.; Vanella, D.; Iovino, M. Artificial Neural Networks for Predicting the Water Retention Curve of Sicilian Agricultural Soils. *Water* **2018**, *10*, 1431. <https://doi.org/10.3390/w10101431>.
20. Vereecken, H.; Weynants, M.; Javaux, M.; Pachepsky, Y.; Schaap, M.G.; Van Genuchten, M.T. Using Pedotransfer Functions to Estimate the van Genuchten–Mualem Soil Hydraulic Properties: A Review. *Vadose Zone J.* **2010**, *9*, 795–820. <https://doi.org/10.2136/vzj2010.0045>.
21. Šimůnek, J.; Van Genuchten, M.T.; Šejna, M. HYDRUS: Model Use, Calibration, and Validation. *Trans. ASABE* **2012**, *55*, 1263–1276. <https://doi.org/10.13031/2013.42239>.
22. Bouyoucos, G.J. Directions for Making Mechanical Analysis of Soils by the Hydrometer Method. *Soil Sci.* **1936**, *42*, 225–230. <https://doi.org/10.1097/00010694-193609000-00007>.

23. Allen, R.G.; Pereira, L.S.; Raes, D.; Smith, M. *Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56*; FAO—Food and Agriculture Organization of the United Nations: Rome, Italy, 1998.
24. Markovic, M.; Filipovic, V.; Legovic, T.; Josipovic, M.; Tadic, V. Evaluation of Different Soil Water Potential by Field Capacity Threshold in Combination with a Triggered Irrigation Module. *Soil Water Res.* **2015**, *10*, 164–171. <https://doi.org/10.17221/189/2014-SWR>.
25. Food and Agriculture Organization of the United Nations. *Standard Operating Procedure for Saturated Soil Paste Extract*; Food and Agriculture Organization of the United Nations: Rome, Italy, 2021.
26. Feddes, R.A.; Zaradny, H. Model for Simulating Soil-Water Content Considering Evapotranspiration—Comments. *J. Hydrol.* **1978**, *37*, 393–397. [https://doi.org/10.1016/0022-1694\(78\)90030-6](https://doi.org/10.1016/0022-1694(78)90030-6).
27. Vrugt, J.A.; Van Wijk, M.T.; Hopmans, J.W.; Šimunek, J. One-, Two-, and Three-dimensional Root Water Uptake Functions for Transient Modeling. *Water Resour. Res.* **2001**, *37*, 2457–2470. <https://doi.org/10.1029/2000WR000027>.
28. Kandelous, M.M.; Šimunek, J.; van Genuchten, M.T.; Malek, K. Soil Water Content Distributions between Two Emitters of a Subsurface Drip Irrigation System. *Soil Sci. Soc. Am. J.* **2011**, *75*, 488–497. <https://doi.org/10.2136/sssaj2010.0181>.
29. Burke, W.; Gabriels, D.; Bouma, J. *Soil Structure Assessment*; A.A. Balkema: Rotterdam, The Netherlands, 1986.
30. Dane, J.H.; Hopmans, J.W. Pressure Plate Extractor. In *Methods of Soil Analysis: Physical Methods, Part 4, Physical Methods*; Dane, J.H., Topp, G.C., Eds.; Soil Science Society of America: Madison, WI, USA, 2002.
31. Van Genuchten, M.T. A Closed-form Equation for Predicting the Hydraulic Conductivity of Unsaturated Soils. *Soil Sci. Soc. Am. J.* **1980**, *44*, 892–898. <https://doi.org/10.2136/sssaj1980.03615995004400050002x>.
32. Radcliffe, D.E.; Šimunek, J. *Soil Physics with HYDRUS: Modeling and Applications*; CRC Press: Boca Raton, FL, USA, 2018.
33. Gelhar, L.W.; Welty, C.; Rehfeldt, K.R. A Critical Review of Data on Field-scale Dispersion in Aquifers. *Water Resour. Res.* **1992**, *28*, 1955–1974. <https://doi.org/10.1029/92WR00607>.
34. Anderson, M.P.; Cherry, J.A. Using Models to Simulate the Movement of Contaminants through Groundwater Flow Systems. *Crit. Rev. Environ. Sci. Technol.* **1979**, *9*, 97–156. <https://doi.org/10.1080/10643387909381669>.
35. Jury, W.A.; Roth, K.; Jury, W.A. *Transfer Functions and Solute Movement Through Soil: Theory and Applications*; Birkhäuser: Basel, Switzerland; Boston, MA, USA; Berlin, Germany; Stuttgart, Germany, 1990.
36. Šimunek, J.; Van Genuchten, M.T.; Šejna, M. Recent Developments and Applications of the HYDRUS Computer Software Packages. *Vadose Zone J.* **2016**, *15*, vzj2016-04. <https://doi.org/10.2136/vzj2016.04.0033>.
37. Willmott, C.J. On the validation of models. *Phys. Geogr.* **1981**, *2*, 184–194. <https://doi.org/10.1080/02723646.1981.10642213>.
38. Gupta, H.V.; Sorooshian, S.; Yapo, P.O. Status of Automatic Calibration for Hydrologic Models: Comparison with Multilevel Expert Calibration. *J. Hydrol. Eng.* **1999**, *4*, 135–143. [https://doi.org/10.1061/\(ASCE\)1084-0699\(1999\)4:2\(135\)](https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135)).
39. Hu, Q.; Yang, Y.; Han, S.; Yang, Y.; Ai, Z.; Wang, J.; Ma, F. Identifying Changes in Irrigation Return Flow with Gradually Intensified Water-Saving Technology Using HYDRUS for Regional Water Resources Management. *Agric. Water Manag.* **2017**, *194*, 33–47. <https://doi.org/10.1016/j.agwat.2017.08.023>.
40. Tlig, W.; Mokh, F.E.; Autovino, D.; Iovino, M.; Nagaz, K. Carrot Productivity and Its Physiological Response to Irrigation Methods and Regimes in Arid Regions. *Water Supply* **2023**, *23*, 5093–5105. <https://doi.org/10.2166/ws.2023.304>.
41. Wang, Z.; Li, J.; Li, Y. Simulation of Nitrate Leaching under Varying Drip System Uniformities and Precipitation Patterns during the Growing Season of Maize in the North China Plain. *Agric. Water Manag.* **2014**, *142*, 19–28. <https://doi.org/10.1016/j.agwat.2014.04.013>.
42. Karandish, F.; Šimunek, J. A Comparison of the HYDRUS (2D/3D) and SALTMed Models to Investigate the Influence of Various Water-Saving Irrigation Strategies on the Maize Water Footprint. *Agric. Water Manag.* **2019**, *213*, 809–820. <https://doi.org/10.1016/j.agwat.2018.11.023>.
43. Crevoisier, D.; Popova, Z.; Mailhol, J.C.; Ruelle, P. Assessment and Simulation of Water and Nitrogen Transfer under Furrow Irrigation. *Agric. Water Manag.* **2008**, *95*, 354–366. <https://doi.org/10.1016/j.agwat.2007.10.021>.
44. Ebrahimian, H.; Liaghat, A.; Parsinejad, M.; Playán, E.; Abbasi, F.; Navabian, M. Simulation of 1D Surface and 2D Subsurface Water Flow and Nitrate Transport in Alternate and Conventional Furrow Fertigation. *Irrig. Sci.* **2013**, *31*, 301–316. <https://doi.org/10.1007/s00271-011-0303-3>.
45. Ranjbar, A.; Rahimkhoob, A.; Ebrahimian, H.; Varavipour, M. Simulation of Nitrogen Uptake and Distribution under Furrows and Ridges during the Maize Growth Period Using HYDRUS-2D. *Irrig. Sci.* **2019**, *37*, 495–509. <https://doi.org/10.1007/s00271-019-00627-5>.

46. El Mokh, F.; Nagaz, K.; Masmoudi, M.M.; Mechlia, N.B. Yield and Water Productivity of Drip-Irrigated Potato under Different Nitrogen Levels and Irrigation Regime with Saline Water in Arid Tunisia. *Am. J. Plant Sci.* **2015**, *06*, 501–510. <https://doi.org/10.4236/ajps.2015.64054>.
47. Hanson, B.; Hopmans, J.W.; Šimůnek, J. Leaching with Subsurface Drip Irrigation under Saline, Shallow Groundwater Conditions. *Vadose Zone J.* **2008**, *7*, 810–818. <https://doi.org/10.2136/vzj2007.0053>.
48. Mguidiche, A.; Provenzano, G.; Douh, B.; Khila, S.; Rallo, G.; Boujelben, A. Assessing Hydrus-2D to Simulate Soil Water Content (SWC) and Salt Accumulation Under an SDI System: Application to a Potato Crop in a Semi-Arid Area of Central Tunisia. *Irrig. Drain.* **2015**, *64*, 263–274. <https://doi.org/10.1002/ird.1884>.
49. Baiamonte, G.; Alagna, V.; Autovino, D.; Iovino, M.; Palermo, S.; Vaccaro, G.; Bagarello, V. Influence of Soil Hydraulic Parameters on Bulb Size for Surface and Buried Emitters. *Agric. Water Manag.* **2024**, *295*, 108756. <https://doi.org/10.1016/j.agwat.2024.108756>.
50. Phogat, V.; Skewes, M.A.; Cox, J.W.; Sanderson, G.; Alam, J.; Šimůnek, J. Seasonal Simulation of Water, Salinity and Nitrate Dynamics under Drip Irrigated Mandarin (*Citrus reticulata*) and Assessing Management Options for Drainage and Nitrate Leaching. *J. Hydrol.* **2014**, *513*, 504–516. <https://doi.org/10.1016/j.jhydrol.2014.04.008>.
51. Zeng, W.; Xu, C.; Wu, J.; Huang, J. Soil Salt Leaching under Different Irrigation Regimes: HYDRUS-1D Modelling and Analysis. *J. Arid Land* **2014**, *6*, 44–58. <https://doi.org/10.1007/s40333-013-0176-9>.
52. Corwin, D.L.; Rhoades, J.D.; Šimůnek, J. Leaching Requirement for Soil Salinity Control: Steady-State versus Transient Models. *Agric. Water Manag.* **2007**, *90*, 165–180. <https://doi.org/10.1016/j.agwat.2007.02.007>.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.