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Research Article

Effect of Evapotranspiration on Soil Moisture Dynamics in Top Surface Layer of a Loamy Land in Climate Change Condition

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Evapotranspiration affects uncertain changes in volumetric soil moisture content (θ) of earth surface, which is considerably controlled by temporal variability of weather parameters like rainfall and ambient temperature. Accurate measurement of temporal variation and spatial distribution of θ in a particular land is very challenging. Numerical modelling with any suitable computer code might be useful in such cases. Thus, Hydrus 2D modelling of θ variation in the soil at Odisha University of Agriculture and Technology (OUAT) in Bhubaneswar is undertaken as main objective of present study to investigate soil moisture dynamics in top surface layer. For the study, the θ in OUAT land was measured daily by 5 TM water content sensor for the duration of two years spanning from January 2021 to December 2022. Meteorological data for these 2 years are collected from a nearby weather station at OUAT and used for calculating evapotranspiration (ET) based on five different well known ET models. Soil hydraulic parameters of OUAT land were also evaluated by laboratory investigation. The evapotranspiration so calculated along with precipitation and materials properties were then assigned as the inputs in Hydrus 2D simulations. The simulated results are found to be in good agreement with field observations. It is proven by Pearson's coefficient of determination (R2) and Nash-Sutcliffe efficiency (NSE) which are found to be 0.83 and 0.84 respectively. The soil moisture simulation was the most accurate only when measured soil parameters along with atmospheric boundary involving Penman-Monteith (PM) ET model were considered as model inputs.

Keywords: soil moisture, evapotranspiration model, simulation, weather data, hydraulic parameter

1 Introduction

Modern improvement of economy and human lifestyle leads to a growing requirement of water resources. The current trends in such global advancement result in experiencing the water scarcity due to many factors like global warming, population growth, rapid urbanization and heavy industrialization, increased energy use, increased irrigation associated with advances in agricultural productivity. The supply, demand, use, availability, and quality of natural water resources depend upon in-depth understanding of these influencing factors (Singh & David, 2002). These factors can also be attributed to the global climate changes. The soil mass along with its volumetric water content of an agricultural land are the fundamental requirements and production resources for breeding of animal and growing of plant to balance the ecosystem of this planet (Jenny, 2012). The changes in volumetric soil water content considerably affect the surrounding ecosystem (Tárník & Igaz, 2015). These changes induce the heat fluxes between the earth surface and atmosphere, basically occurred due to the impact of various weather parameters like precipitation, temperature, humidity, wind speed, and solar radiation. The water conditions of surface and subsurface, hydrological and energetic balance of any given land mainly depends on the soil water storage of its aeration zone or root zone. The quantification, spatial and temporal interpretation of soil water storage are considered crucial for a correct hydrological zonation of agricultural lands (Tárník & Igaz, 2017). Water dynamics within the vadose zone of any watershed is found to be very complicated due to the heterogeneous nature of soil and variable atmospheric boundary conditions at the soil surface (Saifadeen & Gladneyva, 2012). It necessitates

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a holistic approach to be utilized for the determination of overall watershed response to both water demands and climate changes.

The watershed modelling of any river catchment is very essential for better understanding of surface and subsurface water movement and the interactions between these water bodies (Daniel et al., 2011). More importantly, the results from watershed modelling can be employed as the tools for guiding to make decision on water resources, water quality, agricultural management, and related hazard issues. Several research works took attempts to explore the use and challenges of a watershed-based approach wherein various watershed modelling methods, and the key processes involved were discussed minutely. These previous works include data acquisition by remote sensing and space technology, geographic information and data management systems, topographic representation, upscaling of hydrologic conservation equations, spatial variability of infiltration and precipitation, spatial and temporal scaling, model calibration. A great deal of attention was mainly given to model construction, calibration, and data processing while model validation, error propagation, and analyses of uncertainty, risk, and reliability have not been treated as thoroughly.

The hydrologic processes of a watershed area are simulated by the watershed model in a more holistic approach as compared to many other models. Primarily it focuses on individual or multiple processes at relatively small or field-scale without full incorporation of a watershed area. Watershed modelling has emerged as an important scientific research tool for understanding and predicting the water movements, irrigation and pollution in an agricultural land (Melone et al., 2005). Borah and Bera (2003) provided a detailed summary of many of the watershed modelling tools such as Agricultural Non-Point Source Pollution Model (AGNPS), Areal Non-Point Source Water-shed Environment Simulation (ANSWERS), Kinematic Runoff and Erosion Model (KINEROS), Hydrological Simulation Program-FORTRAN (HSPF), MIKE SHE, Soil and Water Assessment Tool (SWAT). However, the HYDRUS 2D code can also be utilized for predicting soil moisture dynamics and watershed modelling. Tarnik and Igaz (2017) used HYDRUS 1D model for checking the validity of output results from the mathematical model for obtaining soil moisture data of Nitra river watershed in Slovakia. Nanda et al. (2018) used the runoff, rainfall, and soil moisture data for calibrating various input parameters of HYDRUS 2D for overland flow model to simulate the runoff hydrograph and soil moisture of Himalayan watershed in India. The modelling results were found to be within the satisfactory range. Wang et al. (2013) commendably employed the computer software package HYDRUS 2D to evaluate the soil water distribution around an emitter in a silt loam soil. Good correspondence between simulations and field observations was noted for investigating and designing drip irrigation management practices.

These aforementioned applications indicate the importance of soil moisture assessments at local, regional, and global scale. Hence, comprehensive knowledge and good expertise for analysing soil moisture evaluation at different scales is essential for improving productivity of agricultural soil and its crop yield, and for monitoring flood and drought. Presently, three main approaches are adopted to capture soil moisture flow:

1. *in situ* measurements (Shaikh et al., 2019),
2. remote sensing technique (Mohanty et al., 2017),
3. hydrological modelling applications (Brocca et al., 2017).

The most precise method to determine soil moisture is direct *in-situ* measurement method where soil sampling devices or varieties of electronic sensors developed based on different techniques (Vereecken et al., 2014) are used. However, it is a tedious, expensive and laborious method to capture the spatial and temporal variability of soil moisture at a larger scale (Srivastava et al., 2019).

2 Material and methods

2.1 Location for research study

Experimental area chosen for this study is Odisha University of Agriculture and Technology (OUAT) located at Bhubaneswar of Odisha state in India. Fig. 1 pictorially presents the exact location of the study area bounded by four borders, North border with 20° 15′ 52.24″ N, South border with 20° 10′ 35.64″ N, West border with 85° 49′ 28.3404″ E, East border 85° 54′ 37.24″ E. OUAT has a Tropical monsoon type of climate. It is one of the warmest regions in India with an average daily high temperature of 32 °C.

2.2 Collection of meteorological and soil moisture data

Meteorological data for 2 years spanning from January 2021 to December 2022 are collected from a nearby weather station at OUAT and used for calculating evapotranspiration (ET) based on five different well known ET models shown in Table 1. Soil hydraulic parameters of OUAT land summarized in Table 2 were also evaluated by the laboratory investigation. The evapotranspiration so calculated along with precipitation and materials properties were then assigned as the input in Hydrus simulations. The volumetric soil moisture content

Figure 1 Pictorial view of the study area

Table 1 Various Models used in the study for computing evapotranspiration (ET)

Designation	Details of different evapotranspiration (ET) models
PM	$ET = \dfrac{\Delta(R_n - G) + p_a c_p (\delta e) g_a}{\left\{\Delta + \gamma\left(1 + {g_a}/{g_s}\right)\right\} LV_v}$
JH	$ET = \dfrac{C_t (T_a - T_x) R_s}{L}$
HS	$ET = \dfrac{0.0023(T_a + 17.8)\sqrt{(T_{\max} - T_{\min})} R_s}{\gamma}$
BC	$ET = p(0.457\, T_a + 8.128)$
PT	$ET = \dfrac{Ls(R_n - G)a}{\gamma}$

Notes: Δ – rate of change of saturation specific humidity with air temperature (MJ.m^{-3}); R_n – net solar radiation (W.m^{-2}); G – ground heat flux (W.m^{-2}), ρ_a – dry air density (kg.m^{-3}); c_p – specific heat capacity of air (J.kg^{-1}.K^{-1}); δ_e – specific humidity (Pa); g_a – atmospheric conductance (m.s^{-1}); g_s – surface conductance (m.s^{-1}); γ – psychrometric constant (Pa.K^{-1}); L_v – volumetric latent heat of vaporization (MJm^{-3}); C_t – temperature coefficient (K^{-1}); R_s – daily solar radiation (W.m^{-2}); T_a – daily mean temperature (°C); T_{max} – daily maximum temperature (°C); T_{min} – daily minimum temperature (°C); T_x – constant for a given area; L – latent heat of vaporization (cal.g^{-1}), p – mean daily percentage of annual daytime hours (%); s – slope of the saturation vapor pressure-temperature relationship (kPa.°C^{-1}); a – Priestley-Taylor coefficient

at two depths 20 cm designated as top layer and 60 cm designated as bottom layer of a soil profile at a hydrological station was measured by 5TM water content sensor with an accuracy of ±0.03 m^3.m^{-3} after its soil specific calibration. Based on the investigation reported by the past researchers (Spelman et al., 2013; Shaikh et al., 2019) 5TM moisture sensor was calibrated in a similar way for this study specifically for each type of soils used for HYDRUS simulation. Soil moisture measurements were taken at an interval of one hour for entire study period. However, hourly soil moisture data were converted to daily average soil moisture data by considering the number of days with valid sensor measurements. Any invalid or negative measurements wherever found due to sensor failure were not considered for the study.

2.3 Numerical simulation

Variation of θ throughout the test soil profile (in two layers) due to environmental conditions for 730 days was simulated using HYDRUS 2D computer code (Šimunek et al., 1999). The software package resolves the following modified Richard's equation (Richards, 1931) of water flow through saturated or unsaturated soil media by finite-element approach.

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x_i}\left[K\left(K_{ij}^A \frac{\partial h}{\partial x_j} + K_{iz}^A\right)\right] - S \qquad (1)$$

where: θ – the volumetric water content (L^3.L^{-3}); h – the pressure head (L); S – a sink term (T^{-1}); x_i (I = 1, 2) – the spatial coordinates (L); t – time (T); K_{ij}^A – the components of a dimensionless anisotropy tensor K^A; K – unsaturated hydraulic conductivity function (LT^{-1}) given by:

$$K(h, x, y, z) = K_s(x, y, z)\, K_r(h, x, y, z) \quad (2)$$

where: K_r – is the relative hydraulic conductivity; K_s – saturated hydraulic conductivity (LT^{-1})

Hydraulic parameters of individual layer soil were computed in the study as input parameters for numerical analyses. These parameters include residual volumetric water content (θ_r), saturated volumetric water content (θ_s), van Genuchten parameters α and n, saturated hydraulic conductivity (K_s), and pore connectivity parameters (l). K_s was determined in the laboratory by falling head permeability test (ASTM D5084-03). Pore connectivity parameter (l) was assumed to be 0.5 for all soil materials based on previous literature (Mualem, 1976).

The hydraulic parameters θ_r, θ_s, α and n were obtained from neural network prediction based on soil textural properties (Wösten et al., 1999). Daily evapotranspiration was computed by using these daily weather data and 5 well-known evapotranspiration models as listed in Table 1. Thus, 5 different sets of atmospheric or time variable boundary condition were considered to the top of surface layer in the numerical modelling. No flux boundary conditions were considered for the vertical sides of the soil profile except for drainage face at the bottom. This drainage face was set as free drainage boundary condition to simulate draining out of water percolated through upper surface layer. Bottom face of the profile was also considered as free drainage boundary condition, which simulates downward movement of percolated water as anticipated in real field scenario. The numerical code estimates temporal spatial variation of θ for the abovementioned initial and boundary conditions, which was compared with the field measurements from respective sensors installed in the test soil profile.

2.4 Calibration of HYDRUS 2D model

In this study, soil moisture flow through a section at 20 cm depth (θ_{20}) of subsurface was considered for elucidating HYDRUS 2D calibration (Šimunek et al., 2012) which was performed in house. The model was calibrated by adjusting θ_s, θ_r, α and *n* based on the agreement in comparison between predicted and observed values of θ_{20}. The HYDRUS 2D embedded inverse modelling estimates the calibrated parameters by fitting measured and simulated soil moisture based on Marquardt-Levenberg optimization algorithm (Marquardt, 1963). Most of the previous researchers (Autovino et al., 2018) calibrated HYDRUS 2D model in this way. During this calibration technique, saturated hydraulic conductivity and empirical parameter n were found to be the most sensitive in predicting water movement, which was also observed in a previous sensitivity study (Kadyampakeni et al., 2018).

2.5 Calibration of HYDRUS 2D model

Two statistical techniques were employed in this study to check the performance capability of HYDRUS 2D model if it can predict soil moisture dynamics with satisfactory and agreeable level of accuracy. Hence, Pearson's coefficient of determination (R^2), Nash-Sutcliffe efficiency (NSE), which can be calculated using Equation 3 and 4 respectively, were employed to evaluate the agreement between HYDRUS 2D simulated values and field observed values of soil water contents. R^2 explains the model accuracy to simulate the field observations. NSE defines the overall reproduction efficiency of the model. For better performance of the model, the criteria need to be the higher value of R^2 (Pearson & Tukey, 1965) and NSE (Nash and Jonh, 1970). Optimum values are 1 for R^2 and NSE, which means the HYDRUS 2D model performs better if R^2 and NSE approaches 1 (Legates & McCabe, 1999).

$$R^2 = \frac{\sum_{i=1}^{n}\left(M_i - \overline{M}\right)\left(S_i - \overline{S}\right)}{\sqrt{\sum_{i=1}^{n}\left(M_i - \overline{M}\right)^2}\sqrt{\sum_{i=1}^{n}\left(S_i - \overline{S}\right)^2}} \quad (3)$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(M_i - S_i\right)^2}{\sum_{i=1}^{n}\left(M_i - \overline{S}\right)^2} \quad (4)$$

where: M_i – measured value; S_i – simulated value; $\overline{M}$ – mean of measured values; $\overline{S}$ – mean of simulated values; n – number of observations

Table 2 Basic characterization of soil materials used for the study

Properties/Parameters	Top soil	Bottom soil
Specific gravity	2.72	2.81
Bulk density (g.cm^{-3})	1.85	1.95
Saturated hydraulic conductivity (m.s^{-1})	$3.64 \cdot 10^{-4}$	$8.47 \cdot 10^{-6}$
Soil type	loam	silt loam
Saturated soil water content (θ_s)	39%	41%
Residual soil water content (θ_r)	8%	7%
Van Genuchten Parameters (α)	0.036	0.021
Van Genuchten Parameters (*n*)	1.57	1.41

3 Results and discussion

3.1 Evaluation of HYDRUS 2D model accuracy

Two statistical parameters were used in this study to quantitatively verify the accuracy of HYDRUS 2D model performance in simulating soil moisture dynamics in OUAT land in Bhubaneswar Odisha The values of these parameters obtained from the statistical analyses of measured and simulated data set, are summarized in Table 3. Based on the calibration of HYDRUS 2D model, range of values of various parameters approached from 0.59 to 0.83 for R^2, from 0.44 to 0.84 for NSE. This changes in the values of these statistical parameters clearly indicates the performance improvement of HYDRUS 2D model in simulating soil moisture dynamics after its satisfactory calibration. The performance of HYDRUS 2D model was similarly evaluated in some previous studies (Wang et al., 2013). Table 3 advocate that the HYDRUS 2D model could successfully simulate the soil moisture after its satisfactory calibration.

3.2 Temporal variation of volumetric soil moisture content

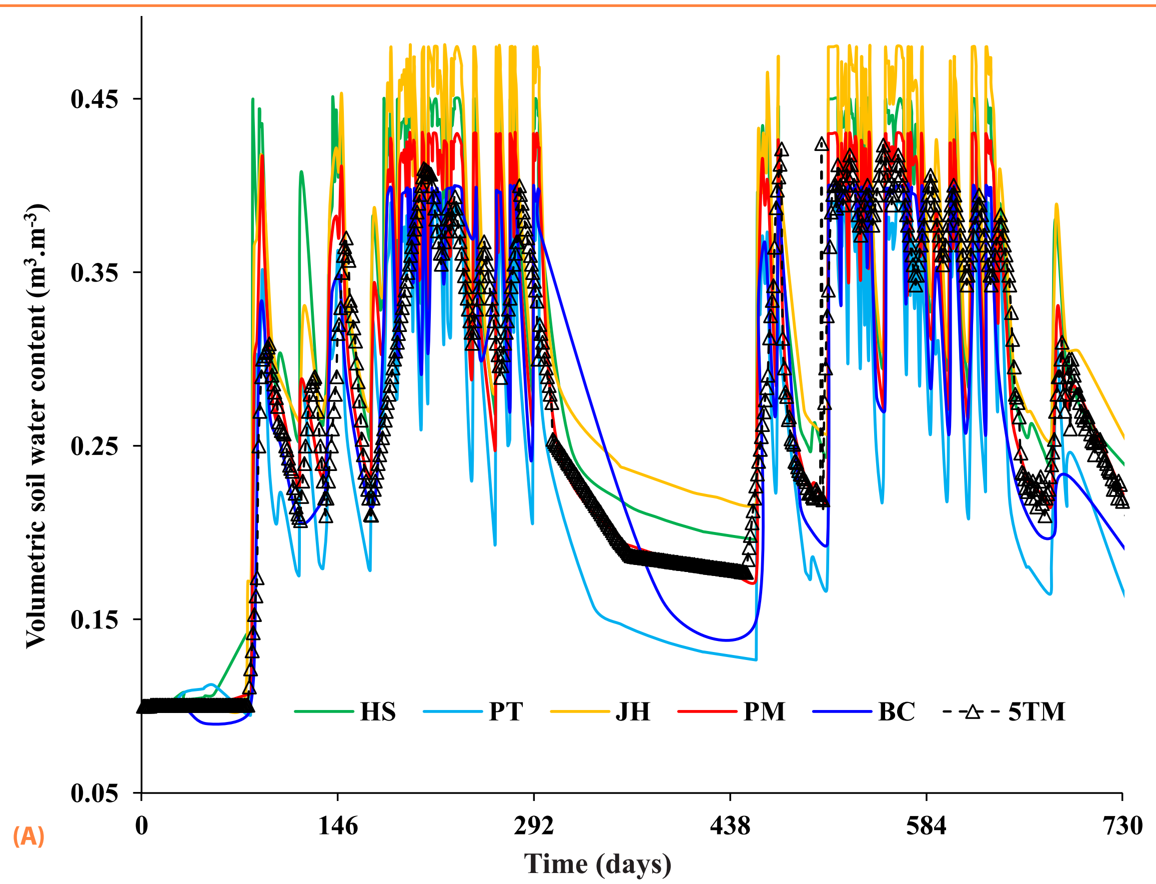
Fig. 2 (A) and (B) demonstrates temporal variation of volumetric moisture content θ respectively in top and bottom soil layers for 730 days ranging from 1st January 2021 to 31st December 2022. The soil moisture variation was simulated in Hydrus 2D software code based on five different ET models (PM, JH, HS, BC and PT) described in Table 1. It can be clearly noted from the Figs 2 (A) and (B) that the volumetric soil moisture in top layer varies seasonally in the range from 0.1 to 0.43 for the top layer and from 0.15 to 0.45 for bottom layer respectively. The Figs 2 (A) and (B) also shows higher and lower moisture content for rainy and summer season respectively in a periodic manner for the two years. There is very marginal variation in results of moisture content predicted based on different ET models. It can be noticed from the Figs 2 (A) and (B) that the soil moisture content never crossed the assumed initial moisture content for entire five years. The Figs. 2 (A) and (B) shows that the θ values simulated based on PM model are in good agreement with measured values. The recurring variation of θ because of alternate wetting and drying events, was noted to be extreme for the topsoil layer indicating considerably high soil-atmosphere interaction. influence of weather gradually diminishes as the depth of θ measurements increases. Consequently, the range of θ variation successively became smaller with the increase in depth of observations. Similar observations were previously made in several studies (Li et al., 2021)

3.3 Spatial variation of volumetric soil moisture content

Fig. 3 (A), (B), (C), (D) and (E) portray the variation of volumetric water content along with the soil profile of depth 100 cm at the end of each of two different years, which were simulated using the five various ET models based on Penman Monteith (PM), Jensen Haise (JH), Priestley Taylor (PT), Hargreaves Samani (HS) and Blaney Criddle (BC) respectively. All these depth wise variations of soil moisture content were compared with the depth wise variation of soil moisture content of the first day which was considered to be initial condition for the numerical simulation. There is very marginal change in the variation trend for all five ET models. All the ET models predict comparable results of water content which varies from 0.08 to 0.32. However, none of simulated results have crossed the initial condition, and water content fluctuation with maximum deviation was noticed in second year whereas the least deviation in the variation of volumetric water content was observed in the first year. The figure compares the results obtained from HYDRUS 2D simulations with their respective measured values captured in the field using 5TM sensor. Simulated values matched very well with measured values. The similar observations were also found in previous literature (Pan et al., 2021).

Table 3 Results of statistical analysis to evaluate HYDRUS 2D model efficiency

Statistical parameters	Soil depth (cm) of moisture variation	Soil water content ($m^3.m^{-3}$)	
		before calibration	after calibration
R^2	20	0.62	0.86
(–)	60	0.56	0.80
Average value of ^{R2}	overall	0.59	0.83
NSE	20	0.43	0.86
(–)	60	0.45	0.82
Average value of NSE	overall	0.44	0.84



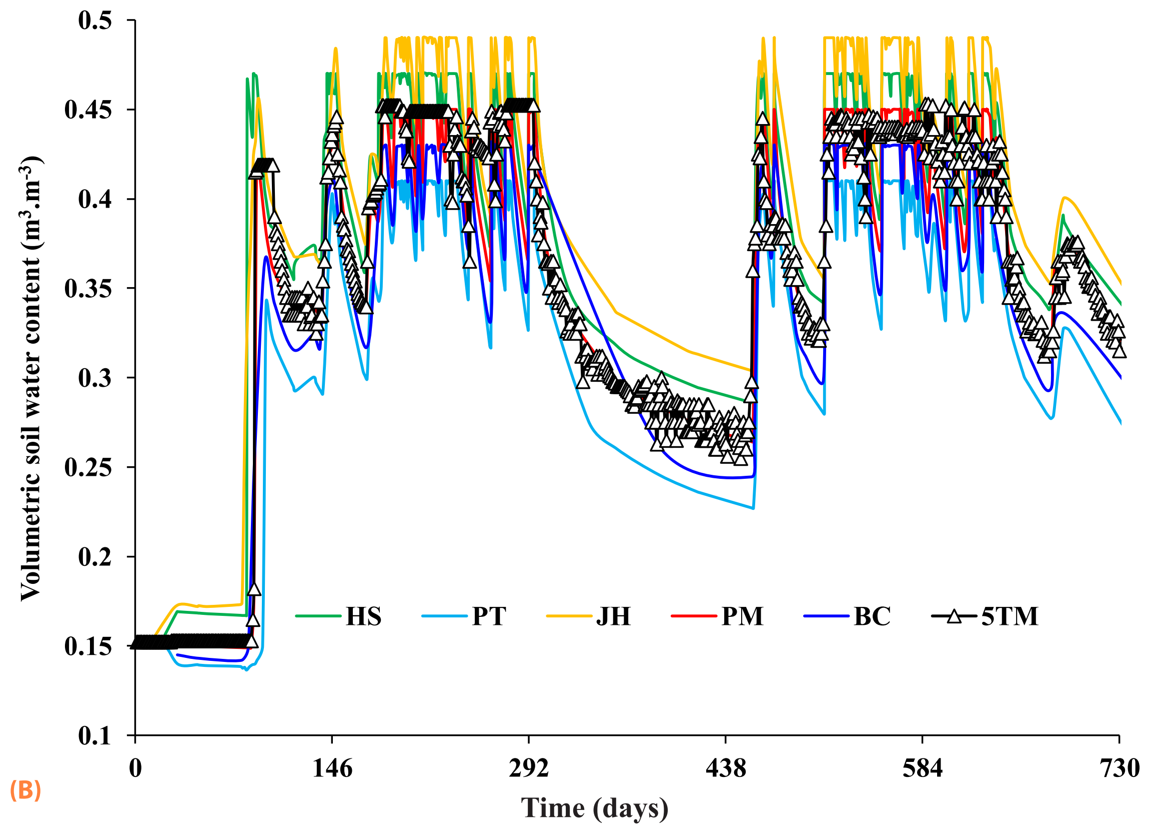


Figure 2 Temporal variation of volumetric soil moisture content in (A) top layer (20 cm) and (B) bottom layer (60 cm) based on different ET models

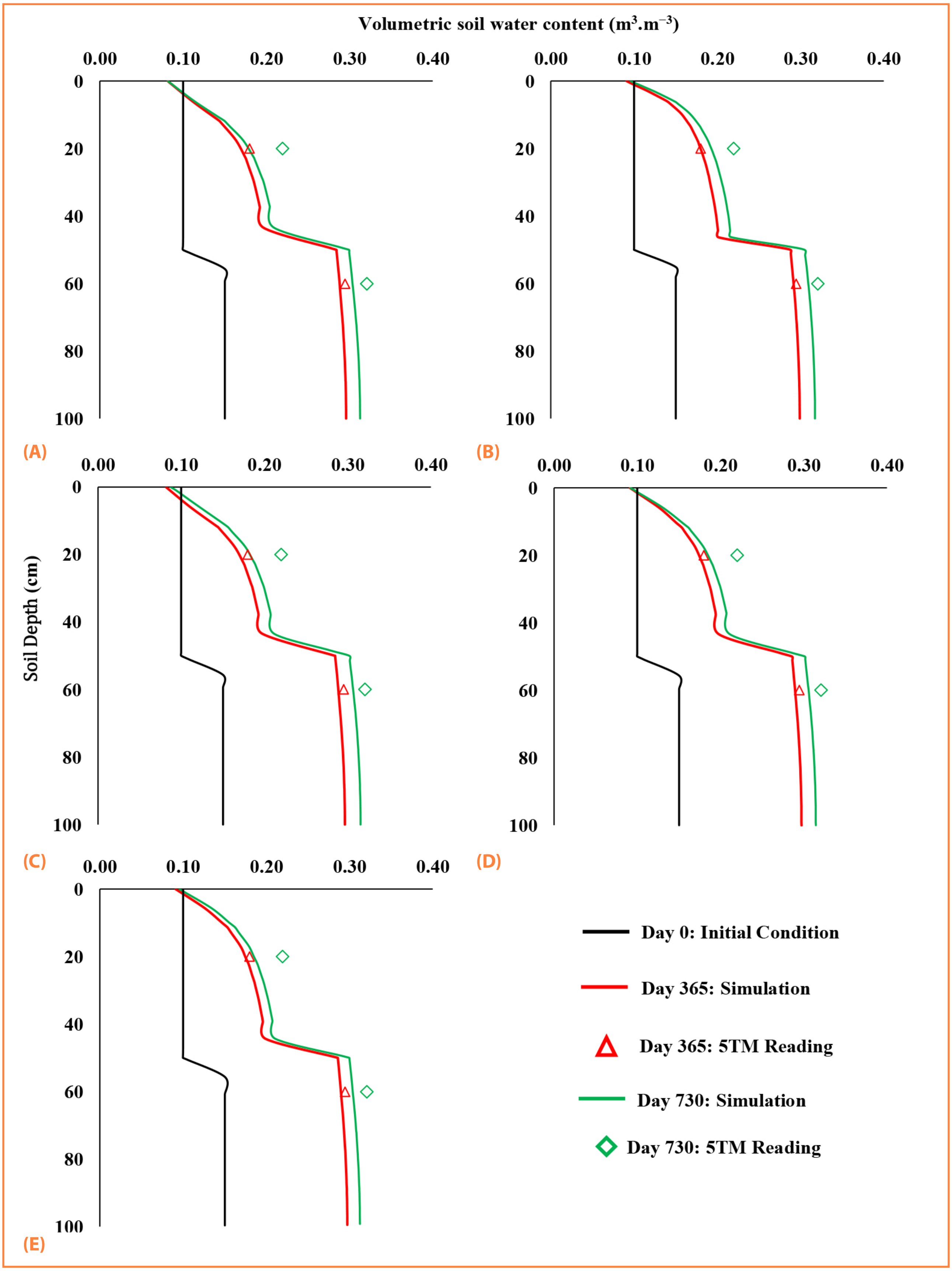


Figure 3 Spatial variation of volumetric soil moisture content using ET models based (A) Penman Monteith, (B) Jensen Haise, (C) Priestley Taylor, (D) Hargreaves Samani and (E) Blaney Criddle

4 Conclusions

- This study demonstrates regional-scale numerical simulation of soil moisture dynamics by employing HYDRUS 2D model at point-scale.
- The study advocates that the HYDRUS 2D reproduces the most precise result if measured soil hydraulic parameters along with atmospheric boundary involving Penman-Monteith model are assigned as the model inputs.
- The study also indicates the effectiveness of HYDRUS 2D model to successfully predict the temporal variation and spatial distribution of soil moisture content (θ) with good agreement.

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