Soil water storage and its temporal association with other water-atmospheric variables in a tomato field under different irrigation regimes

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Abstract: This study was conducted to evaluate the effect of different irrigation regimes on soil water dynamics and temporal associations with other water-atmospheric variables in a tomato field under different drip irrigation regimes in southwestern Nigeria. The experiment was 3×3 randomized complete block design with a split plot arrangement of treatments in three replicates. Irrigation frequencies of applying water every 7, 5 and 3 days designated as F1, F2, and F3, respectively serve as the main plot of the experiment while irrigation depth of 100%, 75% and 50% of crop water requirement (ET_c) designated as D1, D2 and D3 are the sub-plots. During the growing season, soil water storage (SWS) was monitored in soil depths of 0-5, 5-10, 10-20 and 20-30 cm using oven dry method while daily rainfall and crop evapotranspiration (ET_c) were obtained using rain gauge and daily weather data, respectively. Both classical statistics and time series (state-time) analyses were applied to the data of *SWS*, *P* (rainfall + irrigation) and ET_c. Irrigation water regimes significantly (p<0.05) affected SWS. The water stored was highest in the combination of three days interval and 100% ET_c while it was least in the combination of 7 day (weekly) interval and 50% ET_c. There was high amplitude of temporal variability of soil water storage while the maximum SWS was obtained in all depths at 86 days after planting of tomato. There was strong temporal association between SWS and ET_c but not with *P*. Classical regression of SWS from combinations of *P* and *ET* gave low values of coefficient of determination (R^2) (not more than 28.4%) while about 4 times as that value was obtained from state-time analysis. Employing the state-time approach, the effect of irrigation on soil water dynamics and how stored water is related to other variables was clearly recognized. Therefore, the state-time approach can be a specialized statistical tool for evaluating temporal associations among soil properties and processes under different management scenarios.

Keywords: soil water status; classical regression; state-time analysis; irrigation frequency, irrigation depth

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1 Introduction

Drip irrigation is an efficient and preferred method of irrigation because it saves water as the application is directly to plant root zone. It is appropriate for the intensive production of crops such as vegetables, fruits and ornamentals (Smajstrla and Locascio, 1998). In drip irrigation management, frequency of water application is an important component as it modifies the soil moisture status, water root distribution around the emitter, amount of water percolating in the root zone and the amount of water uptake by plants (Assouline, 2002). Unavailability of water is an important factor that can limit corn

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production throughout the growth stages. Gutierrez et al. (2008) reported that unavailability of water negatively affects crop growth by reducing nutrients cycling and uptake. According to Payero et al. (2006), soil moisture stress during any of the plant growth cycle can cause reduction in crop growth and yield. To forestall this, especially in regions where water resources is limited, even in regions where water is dwindling on daily basis due to climate change, strategies are needed to overcome the reduction in crop production and increase the efficiency and adequate use of available water. An advocated approach is the development of irrigation scheduling techniques such as deficit irrigation (Salemi et al., 2011). Deficit irrigation has been reported to save quantifiable amount of water and increased crop water use efficiency (Sezen et al., 2007; Sahin et al., 2015; Awe et al., 2016).

Soil water stored (*SWS*) in the soil profile is an important variable that controls hydrological and biological processes (Choi and Jacobs, 2007). Lei and Mingan (2012) reported that *SWS* is a variable affected by the combined factors of rainfall, infiltration, upward water movement and water uptake by plant roots. Soil moisture is very important in crop production (Awe et al., 2015). For irrigation purpose, the *SWS* capacity is the total amount of water that is stored in the soil within the plant root zone. Soil with high moisture storage capacity assures supply of water during rainfall scarcity period. Soil water content has long been recognized as variable in space due to soil variability and, in time due to climate (Lei and Mingan, 2012). As far as *SWS* is concerned, precipitation intensity and its frequency play an important role in determining soil water movement in term of infiltration and percolation processes (Lee et al., 2007). The knowledge of *SWS* is therefore crucial for rational management of any crop (Western et al., 2004) and as well giving information on environmental aspects of the water cycle (Timm et al., 2011).

The process of evapotranspiration (*ET*) is of great importance in many disciplines, including irrigation system design, irrigation scheduling and drainage studies (Paul et al., 2005). Soil water management by irrigation has been one of the most important factors to increase crop yield (Goncalves et al., 2010). Monitoring of *SWS* and utilization of information on *ET* can provide accurate estimates of daily water use and can assist the irrigation managers in decision making on how much water to apply and when to apply it.

Classical statistical analysis of variance or multiple regressions has been a major approach used by researchers to analyze data. The results from the classical statistics are not always independent and this makes it impossible to apply it in another place. According to Timm et al. (2011), obtaining representative sampling of agricultural fields has led to the development of new sampling schemes. Initially, scientists based their strategies on classical statistics concept but later complemented with other statistical tools and approaches such as geostatistics, neural networks and state-space (time) to examine the data observed at different points for better understanding of the structure and the temporal distribution of soil-plant and other atmospheric variables (Western et al., 2002; Timm et al., 2006; Hu et al., 2008). Thus, this makes the approach of state-time analysis of soil physical and hydraulic properties coupled with other statistical analysis to be more recognized (e.g. Wendroth et al., 2003; Timm et al., 2011; Awe et al., 2014, 2015). Increasing the understanding of the behavior of the soil water status in the profile over time and as it is affected by soil and water management will benefit irrigation engineers, soil scientists and farmers. Therefore, the objectives of this study were to (i) evaluate soil water dynamics in the soil profile and (ii) evaluate the temporal associations between SWS and other soil-atmospheric variables of a drip-irrigated tomato field under different water regimes.

2 Materials and Methods

2.1 Description of study site

The study was carried out at the Teaching and Research field of Agricultural Engineering of Ladoke Akintola University of Technology, Ogbomoso (8°10′N and 4°10′E), Nigeria during the dry season (February–May) of 2014. The field has a gentle slope and the soil is sandy loam texture (Soil Survey Staff, 2010). The maximum and minimum temperature is 33°C and 28°C, respectively. The relative humidity of the area is high (about 74%) all year round except in January when dry wind blows from the north. The annual rainfall of the city area is over 1000 mm (Olaniyi, 2006). Some soil physical and chemical properties of the study site are presented in Table 1.

Table 1 Selected soil physical and chemical properties of the site

Soil depth (cm)	pH	K (cmol/kg)	Ca (cmol/kg)	Mg (cmol/kg)	SOM (%)	BD (g cm^{-3})	Ksat (Mm hr^{-1})	Sand (%)	Silt (%)	Clay (%)	Texture
0-5	7.2	0.6	14.0	2.8	1.8	1.48	52.07	80.5	8.1	11.4	SL
5-10	6.8	0.5	13.0	3.4	1.2	1.62	51.09	77.6	12.0	10.4	SL
10-20	6.6	0.3	11.3	1.6	1.2	1.70	54.10	79.7	10.1	10.2	SL
20-30	6.2	0.4	14.1	2.3	1.0	1.73	50.84	76.3	13.2	11.5	SL

Note: pH: level of alkalinity or acidity; K: potassium; Ca: calcium; Mg: magnesium; SOM: soil organic matter; BD: bulk density; Ksat: saturated hydraulic conductivity; SL: sandy loam

Experimental design, field layout and procedure

A 3×3 randomized complete block design (RCBD) with split plot arrangement of treatments in three replicates was used. Irrigation frequency, F1: weekly interval; F2: five days interval; and F3: three days interval constitutes the main plot while irrigation depths (D1: 100% crop water requirement; D2: 75% crop water requirement; and D3: 50% crop water requirement) are the sub-plots. The main plot was 7×7 m^2, while the sub-plot was 2×2 m^2 with 0.5 m apart. The field was ploughed and harrowed according to normal tillage operation. The field layout is shown in Figure 1. To allow easy transplanting of seedlings the position for the tomato seedlings were marked with pegs according to the recommended spacing of 0.5×1 m (Charlo et al., 2006). Apart from irrigation treatment, all other agronomic and management practices such as weeding, fertilizer application, crop protection and so on remain the same in all the plots and sub-plots throughout the growing cycle.

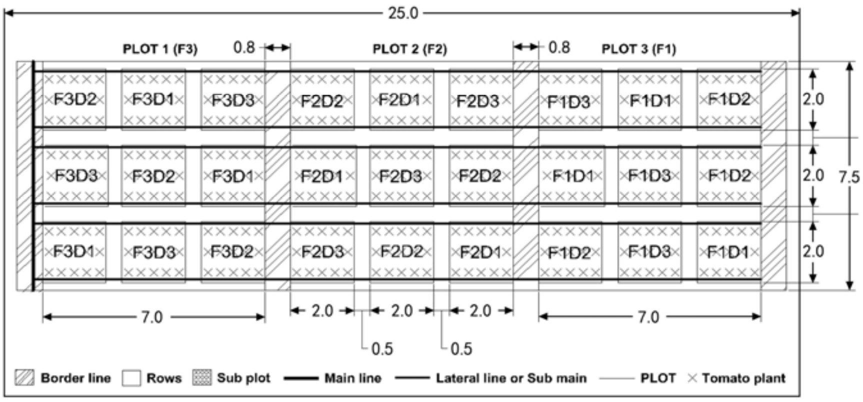


Figure 1 Field layout of tomato drip irrigation experiment site

Note: F1: weekly interval; F2: five days interval; F3: three days interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement.

Physical parameters (soil texture, bulk density and gravimetric water content) of soil sample down to 30 cm depth (0-5, 5-10, 10-20 and 20-30 cm) were determined (the results from 0-5 cm surface layer are presented in this paper). Soil moisture monitoring during the growth cycle were done using gravimetric technique (Krishna, 2002). The volumetric soil moisture was obtained according to USDA (2009) as:

$$\theta_v = \theta_g \times BD \tag{1}$$

where, θ_v is volumetric water content (cm^3 cm^{-3}); θ_g is gravimetric soil water content (g g^{-1}) and BD = bulk density (g cm^{-3}).

The *SWS* in the 0-30 cm profile was computed as:

$$SWS_t = \sum_{i=1}^{n} \theta_{vi} \times Z_i \tag{2}$$

where, SWS_t is the total water stored in the soil profile for a given treatment, mm; θ_{vi} is the volumetric water content in a particular soil layer, cm^{3}cm^{-3}; z_i is the depth of each soil layer, mm; i is the particular soil layer and n is the number of measurement points.

2.2 Weather data, crop evapotranspiration and water balance

Daily minimum and maximum temperature were obtained from a wet- and dry-bulb thermometer while the rainfall depth was obtained using raingauge installed at the center of the field. Daily relative humidity was obtained from psychometric chart using minimum and maximum temperature while the daily reference evapotranspiration was obtained using FAO-ETo Calculator software. Thornthwaite formula (Thornthwaite, 1948) was adopted because of the possibility of using minimum input data.

Daily crop evapotranspiration (ET_c) was computed as:

$$ET_c = K_c \times ET_o \tag{3}$$

where, ET_c is the crop evapotranspiration, mm day^{-1}; K_c is the crop coefficient (vary for different stages of the growth of the crop). Following the procedure described in Allen et al. (1998), the computation of daily K_c for the tomato crop can be found in Ogundipe et al. (2016) and ET_o is the reference evapotranspiration, mm day^{-1}.

3 Data analysis

3.1 Classical statistics

The temporal variability of *SWS* of each treatment at different soil depths (0-5, 5-10, 10-20 and 20-30 cm) was analyzed using statistical functions: mean ($\bar{X}$), standard deviation (*SD*), coefficient of variation (*CV*), minimum and maximum *SWS*. Classical regression was performed using different combinations of observed *SWS*, rainfall + irrigation (*P*) and crop evapotranspiration (ET_c). Where significant, mean values of SWS was separated using Duncan Multiple Range Test (DMRT) at 5% level of probability. All statistics were done in SPSS (v. 20).

3.2 State-time series analysis of soil water storage, precipitation and evapotranspiration

The autocorrelation (AC) and cross-correlation ($r_c(h)$) functions of *SWS*, *P* and ET_c data were obtained using a special state-time algorithm software (STATE.VAR®) for data collected at different time during the growing season. Prior to the state-time analysis, the values of the *SWS*, *P* and ET_c were normalized as described in Hui et al. (1998), that is Z_t data can be normalized with respect to their mean (m) and standard deviation (σ) as:

$$Z_t = \frac{[Z_t - (m - 2\sigma)]}{4\sigma} \tag{4}$$

where, Z_t is the original data and the normalized values of Z_t become dimensionless with normalized mean, μ = 0.5 and normalized standard deviation, δ = 0.25. This transformation allows the state coefficients of matrix ∅ to have magnitudes proportional to their contribution to each state variable to be used in the analysis. To ensure the data set appear in time series manner, zero (0) was used for days when observation was not made. State-time analysis was performed using the special state-algorithm (STATE.EXE®) of the time series data of the surface layer of each treatment (Awe et al., 2015) and state (forecast) equations were developed using different combinations of scaled *SWS*, *P* and ET_c. A comparison was made between the forecast equations obtained by state-time analysis and those from classical regression.

4 Results and Discussion

4.1 Temporal distribution of rainfall, irrigation and evapotranspiration

The temporal distribution of rainfall received, evaporative demand of the atmosphere and ET_c during the growing cycle is presented in Figure 2 while Table 2 shows the total amount of irrigation received by each treatment. Evaporative demand of the atmosphere otherwise known as reference evapotranspiration ranged between 2.76 and 6.05 mm. Crop evapotranspiration was minimum during the early growth stage, it was maximum during the mid-season and subsequently reduced during the late season. The total amount of rainfall received during the period was 453.82 mm (Table 2) while the total ET_c was about 4% lower than rainfall amount (Figure

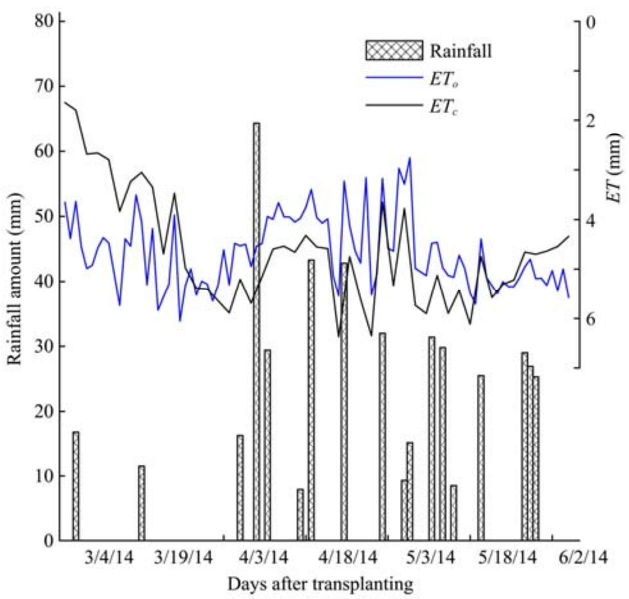


Figure 2 Distribution of rainfall and evaporative demand of the atmosphere (ET_o) during the growing cycle

2). The amount of irrigation applied during the period ranged between 95.98 and 20.18 mm. Rainfall was scarce in the first one month after transplanting, thus total irrigation was practice during the period while supplemental irrigation was applied during periods of frequent rainfall (2nd and 3rd months).

Table 2 Total irrigation amount received by each treatment during the growth cycle

Treatment	F3D1	F3D2	F3D3	F2D1	F2D2	F2D3	F1D1	F1D2	F1D3
Irrigation (mm)	95.98	72.13	48.08	65.19	48.99	32.64	40.36	30.27	20.18

Note: F3: irrigation every 3 days; F2: irrigation every 5 days; F1: irrigation every 7 days; D1: 100% crop water requirement; D2: 75%crop water requirement; D3: 50% crop water requirement.

4.2 Soil water dynamics and variability

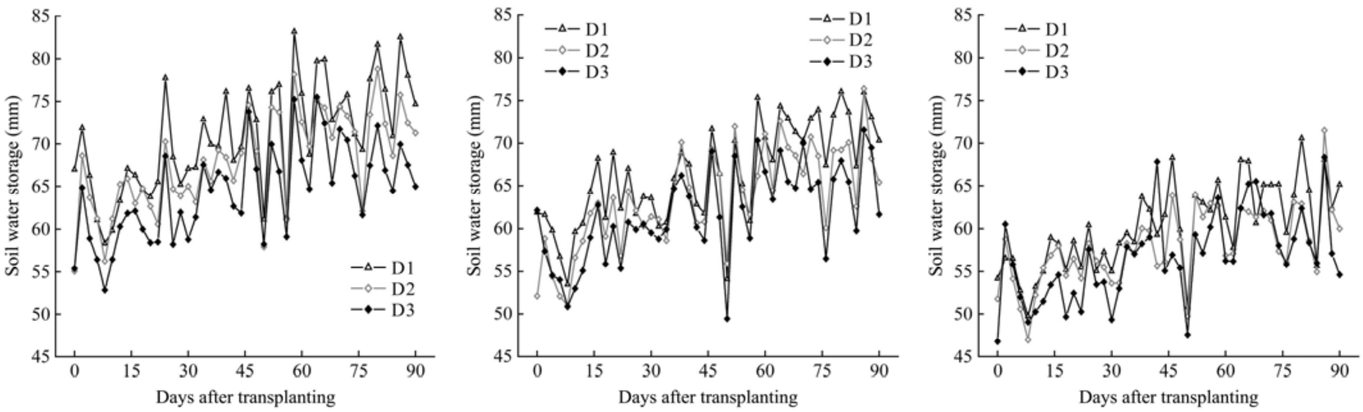
The summary of the temporal distribution of *SWS* in the 0-30 cm profiles shown in Table 3 while Figure 3 shows the temporal distribution of the *SWS*. All the treatments show very high amplitude in the temporal distribution of SWS and there was increasing trend in the profile *SWS* along the growing cycle, strictly following the course of rainfall and irrigation with drying very evident as the frequency of rainfall and irrigation decreases. As the frequency of water application decreases, water stored in the soil profile also decreased. Similarly, deficit irrigation at 50% crop water requirement (D3) had the lowest SWS throughout the growing cycle (Figure 3).

Both the frequency of water application and irrigation depth and their interaction significantly ($p<0.05$) affected *SWS*. The minimum (46.78 mm) and maximum (83.14 mm) values of *SWS* were obtained from F1D3 and F3D1 treatments, respectively while the mean *SWS* was significantly highest (about 71 mm) from F3D1 which was about 20% greater than the water stored under irrigation interval of seven days at 50% crop water requirement (F1D3).

Table 3 Results of descriptive statistics analysis of SWS of the 0-5 cm surface layer of the tomato field under different irrigation regimes

Freq.	Irrigation depth	N	Min.	Max.	Mean.	SD	CV
F3	D1	46	58.32	83.14	70.96±0.186	6.40	0.090
	D2	46	55.08	78.80	67.79±0.147	5.75	0.081
	D3	46	52.86	75.50	64.42±0.150	5.48	0.078
F2	D1	46	53.48	82.90	66.68±0.193	6.28	0.094
	D2	46	51.02	76.41	63.60±0.193	5.87	0.092
	D3	46	49.46	71.56	61.75±0.170	5.38	0.087
F1	D1	46	49.77	70.57	60.19±0.160	4.96	0.082
	D2	46	46.99	71.57	57.97±0.161	4.48	0.077
	D3	46	46.78	68.35	56.67±0.175	5.11	0.090
F (p<0.05)					3.76*		
D (p<0.05)					4.19*		
F×D (p<0.05)					2.98*		

Note: Freq.: Irrigation frequency; F1: weekly interval; F2: five days interval; F3: three days interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement; N: number of sampling campaigns; Min.: minimum value; Max. maximum value; SD: standard deviation; CV: coefficient of variation; F, D: effect of frequency of application and depth of water; F×D: interactive effect of F and D.
* significant at 5% level of probability by Duncan Multiple Range Test (DMRT).
The values after the plus and minus sign are the standard error of mean.



(a) Three days interval (F3) (b) Five days interval (F2) (c) Seven days interval (F1)

Figure 3 Temporal variability of soil water storage (SWS) in the 0-30 cm profile of the tomato field under different irrigation frequency of different days intervals and depth of water application (D)

Note: D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement.

Irrespective of depth of water application, water stored when irrigating every three days (F3) was 6% and 16% greater than that stored when irrigating every five (F2) and seven days (F1), respectively. On the other hand, supplying full crop water requirement (D1) stored water about 4% and 8% more than that stored when supplying 75% (D2) and 50% (D3) crop water requirement. Thus, the trend obtained in terms of water stored was F3D1>F3D2>F2D1>F3D3<F2D2>F2D3>F1D1>F1D2> F1D3. The dispersion of the SWS was very low, not more than 9%.

Profiles of soil water storage on selected days during different growth stages of the tomato crop are shown in Figure 4. Considering the same thickness, water stored in the soil was lower in the 5-10 cm layer than the 0-5 cm surface layer while it was higher in the 10-20 cm layer than 20-30 cm layer during the different growth stages in all the treatments.

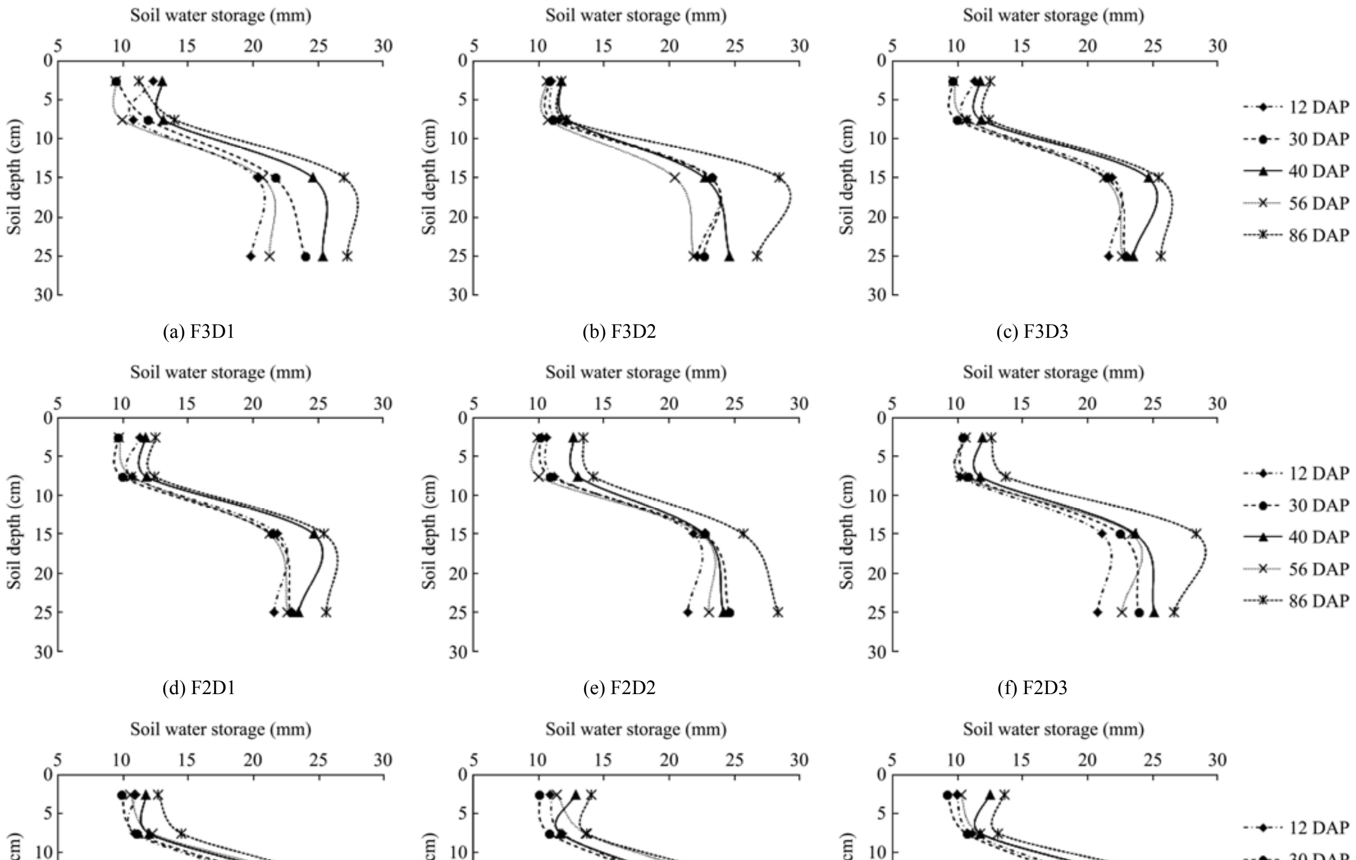


Figure 4 Distribution of soil water storage in the soil layers of treatments during different periods of growth cycle of the tomato crop

Note: F1: three days interval; F2: five days interval; F3: weekly interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement.

Maximum *SWS* was obtained in all depths at 86 days after planting (DAP) and was greater than that observed shortly after planting (12 DAP) for almost all the treatments (Figure 4a-i).

The amount of stored water in a given soil is a variable affected by combined factors of rate of rainfall, irrigation, drainage, run-off and evapotranspiration (Silva et al., 2001; Mota et al., 2010). The high amplitude of the *SWS* in this surface layer is attributed to combined processes of alternate wetting and drying cycles caused by irrigation. During soil wetting (by irrigation or rainfall), the soil water content is increased but subsequently drops as a result of evaporation and transpiration taking place during the drying cycles. The results agree with the findings of Lei and Mingan (2012) and Hu et al. (2010) who observed high temporal variation of SWS at the surface layer compared with deeper soil layers. Similar results were also observed by Choi and Jacobs (2007) within a soil layer of 0-0.25 m.

The differences in SWS observed in the different soil layers may be attributed to preferential uptake of water by plant roots as well as non-homogeneous of the soil structure. For instance, the 20-30 cm layer was not mobilized and thus has its structure more closely packed as indicated by elevated bulk density, resulting in reduced pores responsible for water movement. The higher soil water stored in the surface layer agrees with the findings of Lal (1989) who reported greater water content in the topsoil and attributed it to the fact that crops preferentially abstracts water from depth. The increasing trend in SWS over time is attributed to accumulation of recharge by rainfall and irrigation as well as canopy cover which reduced evaporation from the soil surface.

4.3 Classical regression analysis

The results of the classical linear regressions between *SWS*, rainfall + irrigation (*P*) and crop evapotranspiration (ET_c) for the 0-30 cm profile of the tomato field are shown in Table 4. The regression of *SWS* from only rainfall + irrigation was not significant (p<0.05) for all irrigation treatments while the regression was significant (p<0.05) for ET_c and combination of *P* and ET_c. Using any of *P*, ET_c or their combinations, the variance of the *SWS* of the 0-30 cm profile explained by linear regression for F3 treatment in combination with different levels of crop water requirement ranged between 5% and 24%, the highest value from F3D3 treatment. For F2 treatment, the variance of the measured *SWS* explained varied between 1% and 28%, the highest value from F2D2 treatment while for F1 treatment, the variance of *SWS* explained by linear regression was between 0.5% and 19%, the highest value from F1D1 treatment (Table 4). Generally, from all the treatments (F1, F2 and F3), low values of coefficient of determination were observed when using only *P* or ET_c or their combinations, with the results from combinations of *P* and ET_c twice or thrice that obtained when either of *P* or ET_c was used (Table 4). The result showed that *SWS* could not be satisfactory regressed or predicted from these parameters. Similar observation was reported by Timm et al. (2011) when investigated the temporal variability of soil water storage evaluated for a coffee field. Awe et al. (2015) also observed very low coefficient of determination when estimating *SWS* from soil matric potential (Ψ), *ET* or *P* or their combination with conclusion that the *SWS* could not be satisfactory predicted from those parameters.

Table 4 Classical linear regressions between soil water storage (*SWS*), rainfall + irrigation (*P*) and crop evapotranspiration (ET_c) of the tomato drip irrigated field

Frequency	Depth	Equation	R^2 (%)	Sig
F3	D1	SWS=0.22P+69.86	9.03	0.051
		SWS=1.73ET_c+62.96	9.94	0.034
		SWS=0.27P+2.05ET_c+60.15	22.39	0.004
	D2	SWS=0.16P+70.04	5.20	0.127
		SWS=1.85ET_c+62.24	12.72	0.015
		SWS=0.21P+2.13ET_c+59.95	21.50	0.005
	D3	SWS=0.16P+69.33	4.96	0.137
		SWS=2.01ET_c+60.71	15.26	0.007
		SWS=0.22P+2.32ET_c+58.29	24.51	0.002
F2	D1	SWS=0.13P+71.07	2.84	0.263
		SWS=1.90ET_c+62.88	10.63	0.027
		SWS=0.20P+2.20ET_c + 60.55	16.49	0.021
	D2	SWS=0.08P+70.29	1.16	0.475
		SWS=2.75ET_c+57.93	23.73	0.001
		SWS=0.17P+3.01ET_c+55.93	28.43	0.001
	D3	SWS=0.08P+69.83	1.14	0.478
		SWS=1.55ET_c+62.97	08.64	0.047
		SWS=0.13P+1.76ET_c+61.45	11.70	0.069
F1	D1	SWS=0.05P+70.60	0.51	0.639
		SWS=2.07ET_c+61.22	16.85	0.005
		SWS=0.11P+2.23ET_c+59.97	19.35	0.009
	D2	SWS=0.11P+69.37	3.13	0.239
		SWS=1.55ET_c+62.67	11.04	0.024
		SWS=0.16P+1.80ET_c+60.81	17.36	0.016
	D3	SWS=0.16P+70.14	4.92	0.138
		SWS=1.61ET_c+63.36	8.51	0.049
		SWS=0.22P+1.96ET_c+60.80	16.98	0.018

Note: F3: three days interval; F2: five days interval; F1: weekly interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement; R^2: Coefficient of determination, Sig.: level of significant.

4.4 Autocorrelation, cross-correlation and relationship between SWS and other variables

The temporal autocorrelation (AC) lengths (λ) of soil water storage (*SWS*) and rainfall + irrigation (*P*) are shown in Table 5 while the autocorrelation length (AC) of the crop evapotranspiration (ET_c) is shown in Figure 5. There was strong autocorrelation of *SWS* in all the irrigation treatments as the autocorrelation lengths were greater than one (λ>1). The autocorrelation was lowest (≈4 lags) from F1D2 treatment and highest (≈7 lags) from

F2D2 treatment. Irrespective of irrigation depth, the autocorrelation length of *SWS* when irrigation every 3 days (F3) was about 0.7% and 21% greater than that from irrigating every 5 and 7 days, respectively. In the same vein, supplying water to the field at full crop water requirement (D1) had autocorrelation length about 9% and 25% greater than that obtained from deficit irrigation of 5% and 50% crop water requirement in that order. The combined rainfall and irrigation received by the different irrigation treatments did not autocorrelate as autocorrelation lengths were less than unity (λ<1) whereas the ET_c autocorrelated (λ>1) (Figure 5).

Table 5 Autocorrelation (AC) lengths of SWS of the 0-30 cm profile and precipitation + Irrigation (*P*)

Freq.	Irri. Depth	*SWS*	*P*
F1	D1	5.439	0.029
	D2	6.227	0.035
	D3	5.760	0.031
F2	D1	6.306	0.232
	D2	6.528	0.239
	D3	4.468	0.243
F1	D1	6.330	0.183
	D2	3.838	0.020
	D3	4.209	0.219

Note: Freq.: Irrigation frequency; Irri.: irrigation; F3: three days interval; F2: five days interval; F1: weekly interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement.

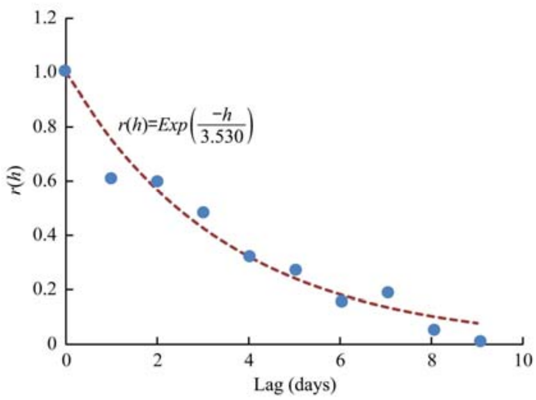


Figure 5 Autocorrelation function of crop evapotranspiration (ET_c) of the drip irrigated tomato

The results of crosscorrelation (CC) between *SWS*, *P* and ET_c are shown in Table 6. *SWS* did not correlate with *P* as crosscorrelation length was less than unity (λ_c<1). Conversely, there was strong correlation between *SWS* and ET_c as λ_c>1. The crosscorrelation length of *SWS* vs ET_c was not completely unique as it ranged between 4.5 and 5.5 lags among the treatments.

Table 6 Crosscorrelation (λ_{cc}) of soil water storage (*SWS*) versus rainfall + irrigation (*P*) and crop evapotranspiration (ET_c)

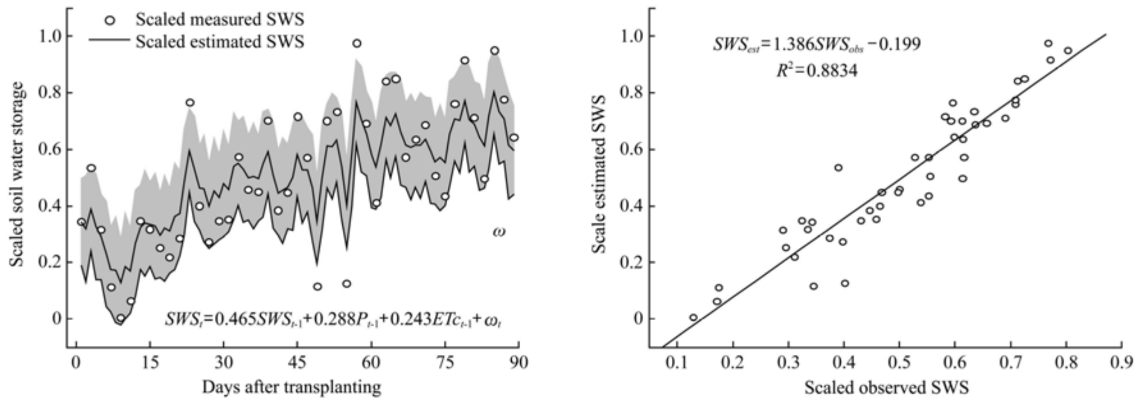
Freq.	Irri. Depth	*SWS* vs *P*	*SWS* vs ET_c
F3	D1	0.593*	4.888
	D2	0.471	5.315
	D3	0.301	5.359
F2	D1	0.683	4.795
	D2	0.644	5.453
	D3	0.676	4.729
F1	D1	0.509	5.456
	D2	0.513	4.489
	D3	0.375	4.759

Note: Freq.: Irrigation frequency; Irri.: irrigation; F3: three days interval; F2: five days interval; F1: weekly interval; D1: 100% crop water requirement; D2: 75% crop water requirement; D3: 50% crop water requirement.

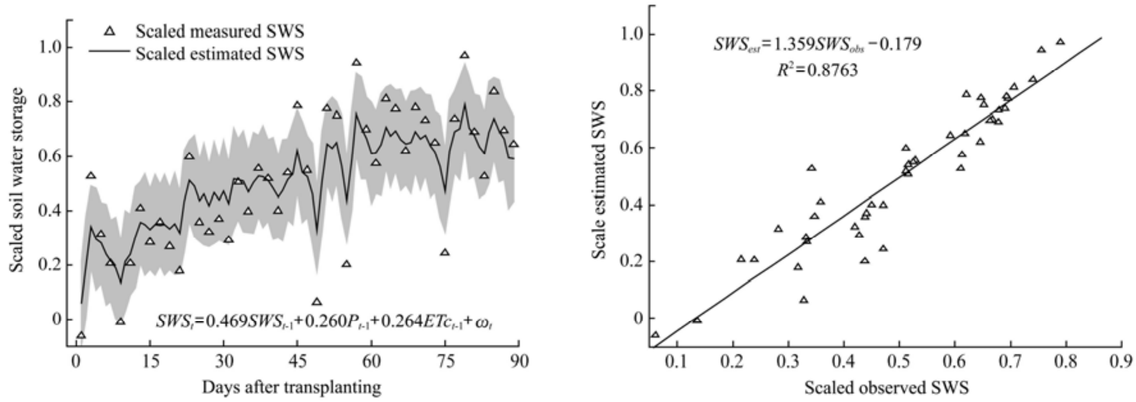
* The crosscorrelation, λ_{cc} was obtained using the relation: $r_c(h) = Exp\left(\frac{-h}{\lambda_{cc}}\right)$, where h is the lag in days. The cross-correlation ($r_c(h)$) functions between *SWS* vs *P* and *SWS* vs ET_c data were obtained using a special state-time algorithm software (STATE.VAR®) for data collected at different time during the growing season.

In term of time series data, the autocorrelation function provides information about the separation period with which a measured value is related to its neighbors and, it is a manifestation of the fact that at or beyond the lag time, observations will vary only randomly (Nielsen and Wendroth, 2003). The AC lengths of greater than one for both *SW*S and ET_c indicate that these variables are related with each other. On the other hand, when the AC lengths are less than one (<1), it shows that there was no correlation, thus they are temporally independent and behave randomly. On the other hand, the degree of linear association between pairs of two different soil properties separated by distance (time) is quantified by their crosscorrelation function, which evaluates the correlation structure of their temporal distributions. It provides quantitative description into the temporal association between two soil properties and deep insight into the temporal covariance structure of the properties (Nielsen and Wendroth, 2003). *SWS* that did not correlate with precipitation (*P*) means that the amount of rainfall and irrigation could be due to alternate wetting and drying cycles due to irregular rainfall and intermittent irrigations during the growing season. The results are in consistence with the findings of Timm et al. (2011) and Awe et al. (2015). It is obvious that the different autocorrelation of SWS and its correlation with other variables showed that the temporal correlation structure of *SWS* measured cannot be uniform under different treatments. Nielsen and Wendroth (2003) and Awe et al. (2015) reported that the autocorrelation and crosscorrelation functions of *SWS* and related properties are not expected to be unique within a field due to variation in intrinsic soil properties, vegetal cover, relief and also with time as a result of management practices, changing and shifting climatic conditions.

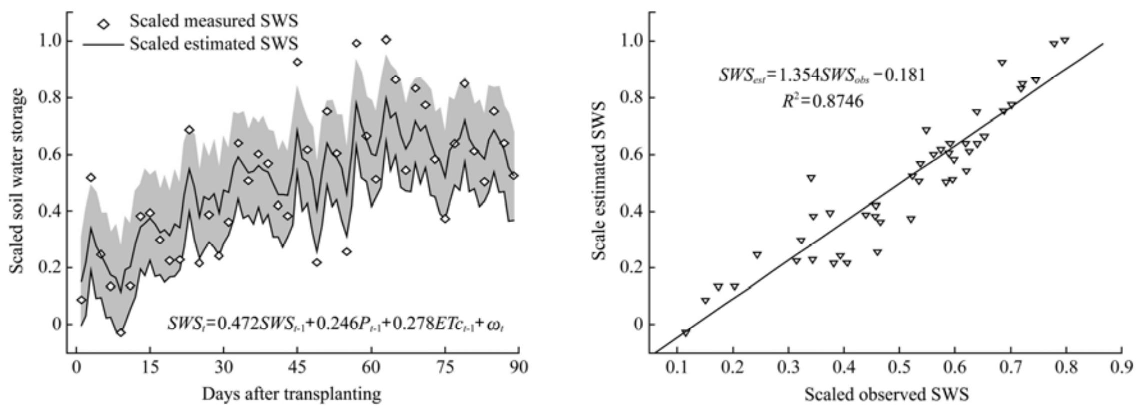
The temporal patterns of the state-time analysis of the scaled soil water storage (*SWS*) 0-30 cm profile for all the treatments and relationship with P and ET_c are presented in Figures 6, 7 and 8. The continuous lines represent the scaled estimated *SWS*, the marked points are the scaled observed data while the shaded region is the 95% fiducial limits which take a plus or minus one standard deviation (mean value ± 1SD) into consideration. About 4-8 out of



(a) 100% crop water requirement (D1)



(b) 75% crop water requirement (D2)

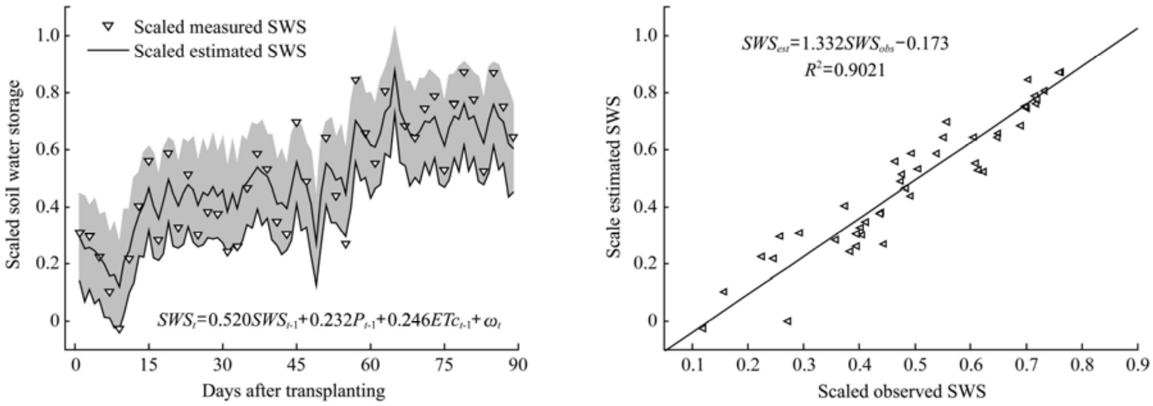


(c) 50% crop water requirement (D3)

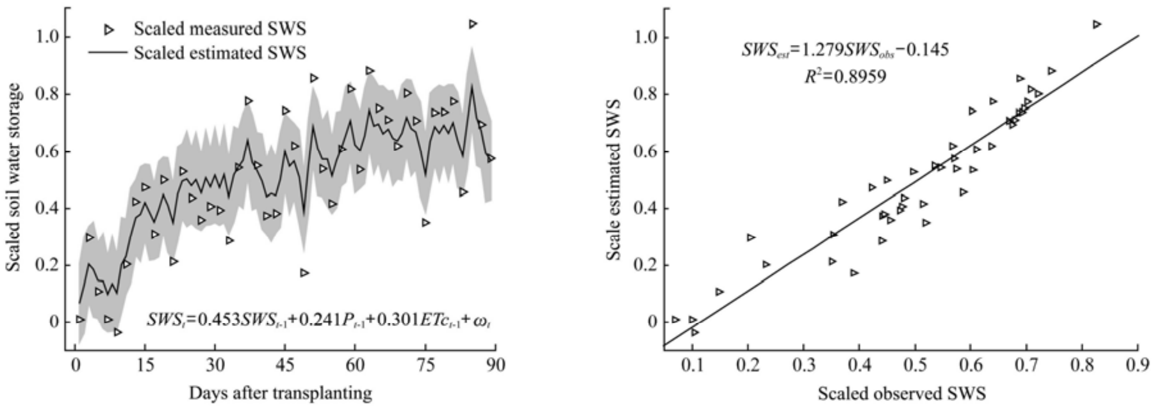
Figure 6 State-time analysis of scaled soil water storage of the 0-30 cm profile, the respective coefficient of determination between scaled observed, and scaled estimated soil water storage of the tomato field irrigated every three days (F3) with water applied at different percent crop water requirement

Note: SWS_t: scaled present soil water storage, mm; SWS_{t-1}: scaled previous soil water storage, mm; P_{t-1}: scaled previous cumulative rainfall + irrigation, mm; ET_{t-1}: scaled previous maximum cumulative evapotranspiration, mm; ωt: error term; SWS_{est}: scaled estimated soil water storage, mm; SWS_{obs}: scaled observed soil water storage, mm. R^2: coefficient of determination.

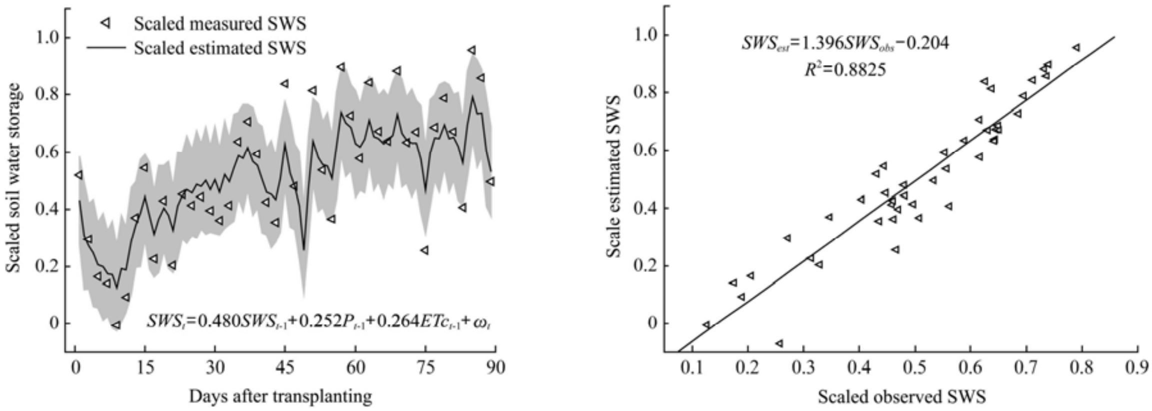
46 measured data were outside the shaded region despite using ± 1SD instead of ± 2SD. In Figure 6, the state equation of F3D1, F3D2 and F3D3 treatment showed that the contributions of each of previous soil water storage ($SWS_{t\text{-}1}$), rainfall + irrigation ($P_{t\text{-}1}$) and crop evapotranspiration ($ET_{t\text{-}1}$) to the estimation of the present soil water storage (SWS_t) was almost at par. The contribution of previous soil water storage ($SWS_{t\text{-}1}$) to the present value of soil water storage (SWS_t) doubled those of P and ET_c showing that SWS depends more on the previous measurements of itself than the previous observations of P and ET_c (Figure 6). Similar trend was obtained for all treatments under F2 and F1 (Figures 7 and 8).



(a) 100% crop water requirement (D1)



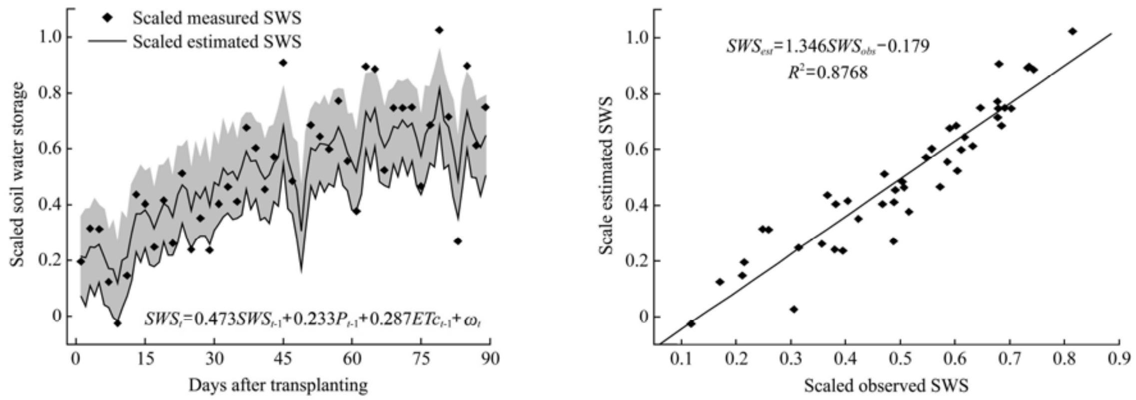
(b) 75% crop water requirement (D2)



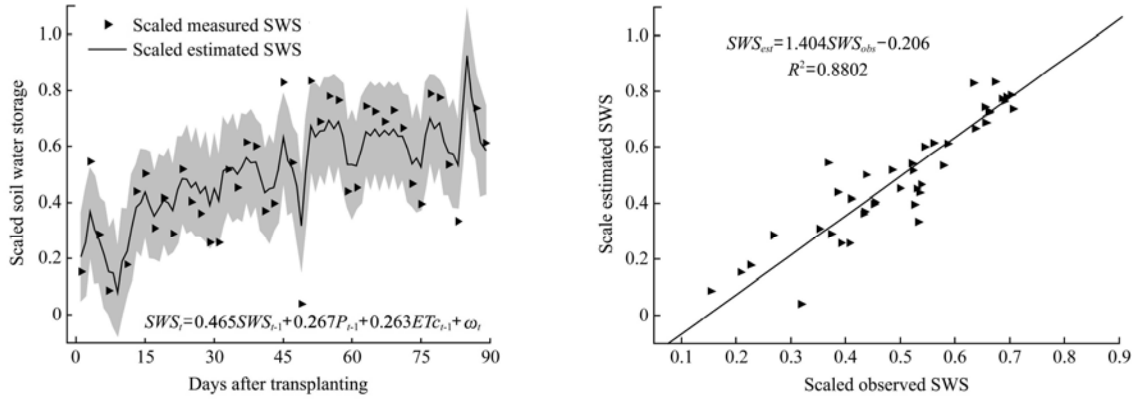
(c) 50% crop water requirement (D3)

Figure 7 State-time analysis of scaled soil water storage of the 0-30 cm profile, the coefficient of determination between scaled observed, and scaled estimated soil water storage of the tomato field irrigated every five days (F2) with water applied at different percent crop water requirement

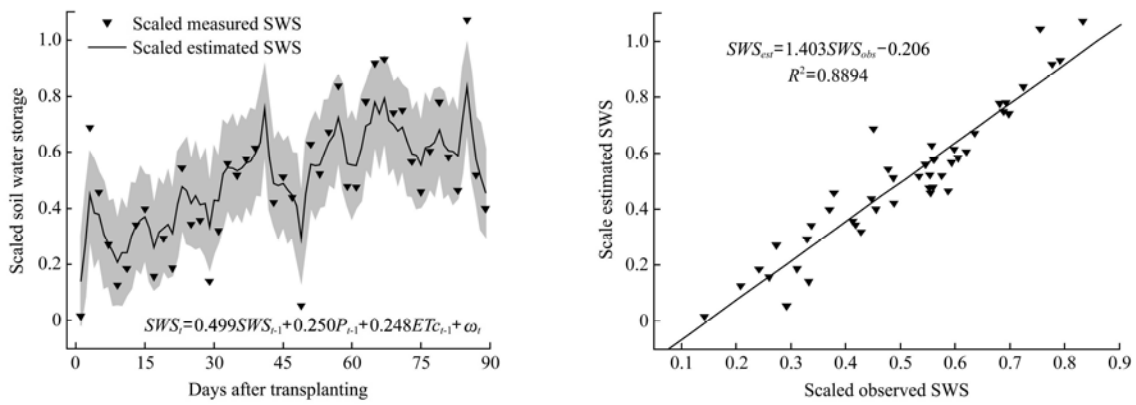
Note: $P_{t\text{-}1}$: scaled previous cumulative rainfall + irrigation, mm; $ET_{t\text{-}1}$: scaled previous maximum cumulative evapotranspiration, mm; ωt: error term; SWS_{est}: scaled estimated soil water storage, mm; SWS_{obs}: scaled observed soil water storage, mm. R^2: coefficient of determination.



(a) 100% crop water requirement (D1)



(b) 75% crop water requirement (D2)



(c) 50% crop water requirement (D3)

Figure 8 State-time analysis of scaled soil water storage of the 0-30 cm profile, the coefficient of determination between scaled observed, and scaled estimated soil water storage of the tomato field irrigated every seven days (F1) with water applied at different percent crop water requirement

Note: P_{t-1}: scaled previous cumulative rainfall + irrigation, mm; ET_{t-1}: scaled previous maximum cumulative evapotranspiration, mm; ωt: error term; SWS_{est}: scaled estimated soil water storage, mm; SWS_{obs}: scaled observed soil water storage, mm. R^2: coefficient of determination.

Considering the temporal relationships between *SWS* and other variables (*P* and ET_c), about 85% of the variance of scaled estimated *SWS* was explained by the use of the state-time analysis under F1 and F3 treatments (Figures 6 and 8). For F2 treatments, the variance explained was slightly higher, ranging between 88% and 90% (Figure 7). Similar results were also reported by Awe et al. (2015) in a study of temporal processes of soil water storage of sugarcane field under different soil and residue management. Using the recommended mean ± 2SD for the fiducial limit instead of ± 1SD used in this study showed that all the data point is within the limit indicating the estimated *SWS* are very good as also reflected by the high coefficient of determination (R^2). The only implication of not using the ± 2SD was that the width of the fiducial limit would be larger. Awe et al. (2015) reported 1 to 2 out of 89 data points outside the fiducial limit when ± 2SD was used, indication the high efficiency of the state-time approach.

In all cases, the contribution of the previous values of cumulative precipitation was more or less the same as that of ET_c, showing the importance of both variables in soil water balance, that is the amount of water stored depends on the amount of rainfall and irrigation water that infiltrates into the soil before being available for evapotranspiration, extraction by plants and transpiration.

Comparing the classical linear regression and the state-time analyses estimate of SWS from combination of *P* and ET_c, the state-time analysis gave higher values coefficients of determination, about 4 times (Table 3 and Figures 6, 7 and 8). These results are in agreement with the findings of similar studies (Dourando-Neto et al., 1999; Timm et al., 2003, 2004, 2011; Awe et al., 2015; Aquino et al., 2015). According to Aquino et al. (2015), since the response of one variable is not unique in a field, in several cases where statistical multiple regression which ignores sampling location coordinates is applied, low coefficients of determination are found.

Another advantage of the state-time over classical regression was that the former considered contribution from its own measurement as well as incorporation of errors accruing from sampling and instrument. Furthermore, state-time analysis gives us a global adjustment of the coefficients that do not represent time to time variations which can lead to interpretations that induce to inadequate management procedures. Employing the state-time approach, we clearly recognize the effect of irrigation on soil water dynamics and how stored water is related to other variables. Therefore, the state-time approach can be a specific statistical tool for evaluating temporal associations among soil properties and processes under different management scenarios.

5 Conclusions

Soil water dynamics and temporal associations of *SWS* with related water-atmospheric variables in a drip-irrigated tomato field were investigated.

Drip irrigation regimes significantly influenced *SWS* of the 0-30 cm profile.

There was temporal variability of *SWS* during the growing season and maximum *SWS* was obtained in all soil layers at the end of the growing season.

Cumulative rainfall and irrigation did not autocorrelate neither did they correlate with SWS whereas both *SWS* and ET_c autocorrelated and crosscorrelated.

Classical linear regressions of *SWS* from rainfall + irrigation (*P*), evapotranspiration (*ET*) and their combination gave poor results in terms of coefficient of determination (R^2).

The state-time approach gave higher coefficient of determination when estimating *SWS* using a combination of *P* and ET_c.

Employing the state-time approach, the effect of irrigation on soil water dynamics and how stored water is related to other variables was clearly recognize. Therefore, the state-time approach can be a specialized statistical tool for evaluating temporal associations among soil properties and processes under different management scenarios and give insight to time to time variations which can lead to interpretations that induce to inadequate management procedures.

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