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Agricultural crop growth modelling: a tool for dealing with the threat of climate change affecting food security (case study for greenhouse tomato)

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ABSTRACT

Climate change and essentiality of the food security have motived scientists to try innovative approaches, among which, crop growth models can help to predict crop yield. In order to simulate tomato (Solanum lycopersicum) growth, phenological characteristics of a short-life variety of tomato were assessed. Phenologic characteristics included leaf area index (LAI), specific leaf area (SLA), crop height (H), leaf fresh and dry weight (LFW and LDW), and stem fresh and dry weight (SFW and SDW). These parameters were measured at four different times (i.e. 33, 45, 55, and 87 days after planting) during tomato growth and development. Fruit fresh and dry weight (FFW and FDW), harvest index (HI), and water efficiency (Ew) were measured at the end of the crop season. This study was done in a randomized complete block design with three levels of irrigation (i.e. at 48h (i1), 72h (i2), and 96h (i3)) in three replications. Irrigation treatment had significant effects on LAI1, LAI2, H2, FLW1, FLW2, DLW1, DLW2, DL2, FSW1, DSW1, DSW2, and DS2 at the 0.01 level, while its effect on SLA1, SLA2, H1, and FSW2 was significant at the level 0.05. Two-tailed correlations among characteristics were investigated and regression models developed for DFW. Dry fruit weight was simulated using both AquaCrop and regression models, separately. It was found that regression model could predict DFW of tomatoes under different treatment better than AquaCrop. It was also concluded that the phenologic characteristics measured at 55 DAP provide good criteria for predicting tomato fruit production.

1- Introduction

Food security, defined as the maximization of self-confidence and social justice for all of the community residents to obtain a safe, culturally acceptable and nutritionally adequate diet through a sustainable food system (Hamm and Bellows, 2003), is one of contemporary major challenges mainly under the effect of climate change (Franzluebbers, 2013). While the world population is increasing, crop models are important tools to develop, implement and maintain food security (Mahajan et al., 2014).

In order to simulate the characteristics of a system, a comprehensive approach based on mathematical models is needed to simulate the system behavior (Rossing et al., 2011). If the crop is considered as a biological system, then crop growth modeling is the mathematical approach to simulate this system in two general ways: 1) empirical models (descriptive, statistical, or regression), in which, experimental data are utilized to find one or more mathematical equations capable of describing the behavior of the system; and 2) mechanistic modeling (also known as explanatory, dynamic or process-based), that involves a quantitative description of the system (Miglietta and Bindi, 1993; Masot Mata et al., 2007; Weiss et al., 2009; Rauff and Bello, 2015).

Descriptive models examine the data, fit an equation or set of equations to them and give no information on the mechanisms that give rise to the response (Rauff and Bello, 2015), thus defining the behavior of a system in a simple manner (Murthy,2004). Based on a differential equation relating growth rate to size, a mechanistic model is usually derived, which is a mathematical relationship representing the mechanism governing the crop growth process (Karkach, 2006). In this study, phenologic characteristics of a short-life tomato variety were measured under controlled conditions based on which two models were developed using regression modelling and the AquaCrop model.

2- Material and Methods

In order to simulate tomato (Solanum lycopersicum) growth under controlled conditions, phenological characteristics of a short-life variety of tomato ('Early Ch.', Canyon, Italy) were assessed in a greenhouse at Tarbiat Modares University, Tehran, Iran (35.74° N, 51.16° E). In order to decrease the effect of probable errors in the experimental results, this study was done in a randomized complete block design and tomatoes were cultivated in 3 treatments of irrigation, each in 3 blocks.

The plants were cultivated in cylindrical pots (with diameter of 30 cm and height equal to 30 cm of which 25cm was filled with soil). Physical properties of the potting soil are reported in Table 1.

Pots were irrigated once every 48h (i_1), 72h (i_2), and 96h (i_3). During the 120 DAP life time of tomatoes, phenological characteristics were measured. The following indices were measured as dependent variables: leaf area index (LAI), specific leaf area (SLA), crop height, leaf fresh/dry weight, and stem fresh/dry weight (in four stages of crop growth and development: vegetative (33 DAP), vegetative-flowering (45 DAP), flowering (55 DAP), and fruiting (87 DAP), respectively), fruit fresh/dry weight, harvest index, and water efficiency (only in fruiting stage (87 DAP)).

Table 1- Pots soil physical properties.

Clay (%)	6	**Electrical Conductivity (dS/m)**	2.7
Silt (%)	16	**pH**	7.2
Sand (%)	78	**Saturation (%)**	21.97
Texture	Loamy Sand	**Field Capacity (%)**	19.7
Bulk Density (gr/cm3)	1.54	**Permanent Wilt Point (%)**	9.3

To measure the plant characteristics, in all the stages, one plant of each replication of each irrigation treatment was selected randomly. The length of the plant was measured as the plant height and the plant shoot was removed. The leaves were separated from the stem, their area was measured (A_l) and they were weighed to give the fresh leaf weight (FLW). Fresh stem weight (FSW) was also measured. In all the stages, the oven-dried weight of leaf and stem was measured.

In the fruiting stage, the fresh fruit weight (FFW), the fresh and oven-dried biomass (leaf, stem, and fruit) weights were measured to determine DLW, DSW, and DFW, respectively. Proportional dry weight of leaf, stem, and fruit (DL, DS, and DF, respectively) was calculated.

In order to calculate the mentioned characteristics, the following equations were used (Masot Mata et al., 2007; Gobron, 2008; Hunt et al., 2013; Li et al., 2017):

$$LAI = \frac{A_l}{A} \qquad (1$$

$$SLA = \frac{A_l}{DLW} \qquad (2$$

$$DL = \frac{FLW - DLW}{FLW} \qquad (3$$

$$DS = \frac{FSW - DSW}{FSW} \qquad (4$$

$$DF = \frac{FFW - DFW}{FFW} \qquad (5$$

$$HI = \frac{DFW}{DLW + DSW + DFW} \qquad (6$$

$$E_W = \frac{FFW}{W} \qquad (7$$

Where: LAI is leaf area index (dimensionless); A_l is the area of each plant leave (mm^2); A is the cross sectional area of each pot (mm^2); SLA is the specific leaf area (cm^2.gr^{-1}); DLW is the leaf dry weight (gr); DL is the proportional leaf dry matter (%); FLW is the leaf fresh weight (gr); DS is the proportional stem dry matter (%); FSW is the fresh stem weight (gr); DSW is the dry stem weight (gr); DF is the proportional fruit dry matter (%); FFW is the fresh fruit weight (gr); DFW is the dry fruit weight (gr); HI is the harvest index (dimensionless); E_w is water efficiency (gr.l^{-1}); and W is the amount of irrigation water in each treatment.

3- Results

As shown in Figure 1, during tomato growth and development, LAI increased under all conditions (treatment and replication), while SLA did not follow this pattern. SLA, at first decreased from 33 to 45 DAP; then, between 45 DAP and 55 DAP, it did not show any specific trend. While i21 and i22 decreased, other treatments-replications increased with different rates.

Meanwhile, plant height increased very fast until the 45th day, then it increased at a lower rate that is due to growth and development from vegetative to productive (flowering) stage. Fresh leaf weight (FLW), dry leaf weight (DLW), leaf proportional dry weight (DL), fresh stem weight (FSW), dry stem weight (DSW), and stem proportional dry weight (DS) all exhibited a general increasing trend, except between 45 and 55 DAP where some rate variations occurred.

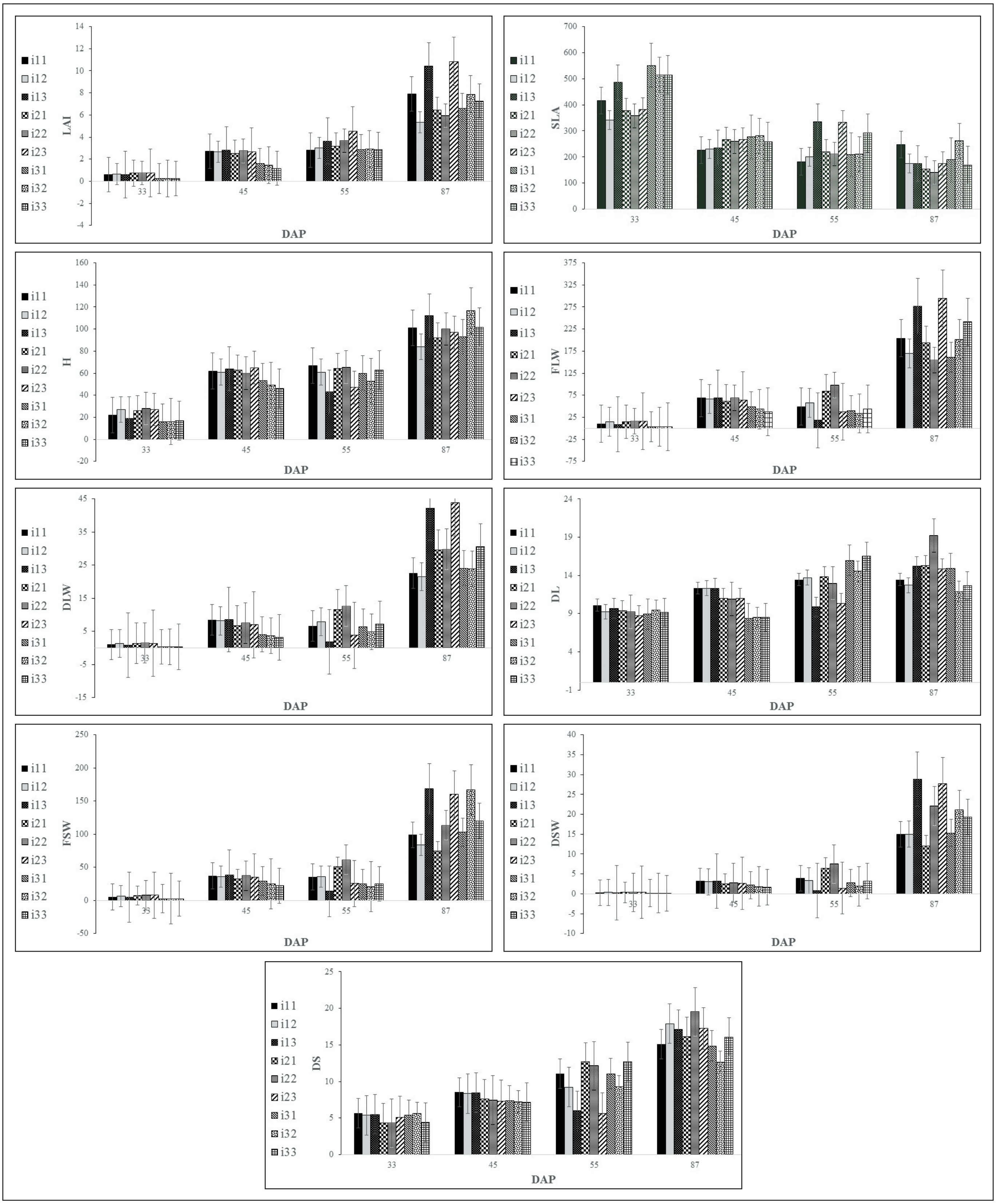

Fig. 1- Changes in parameters measured during tomato growth and development.

Changing rate of tomato plants phenologic characteristics may be due to variation in dry matter partitioning to different organs under the influence of plant growth and development (Zijiang, 2016).

The changes in phenologic trends which occurred between the second and third sampling stages (i.e. 45 and 55 DAP) are not seen in the leaf area index which shows a steady increasing pattern during the entire growth period.

3- 1. Empirical modelling

The irrigation treatment effects were investigated. Analysis of variance (ANOVA) of the treatments under randomized complete block design shows that the irrigation treatment has significant effect on LAI1, LAI2, H2, FLW1, FLW2, DLW1, DLW2, DL2, FSW1, DSW1, DSW2, and DS2 at the level 0.01, while its effect on SLA1, SLA2, H1, and FSW2 is significant at the level 0.05 (Table 2).

Table 2- Significance of the measured parameter.

Parameter	Treatment effect	Replication effect	Parameter	Treatment effect	Replication effect
LAI1	0.000^{**}	0.358	**DL1**	0.297	0.712
LAI2	0.001^{**}	0.896	**DL2**	0.000^{**}	0.588
LAI3	0.077	0.148	**DL3**	0.106	0.340
LAI4	0.897	0.173	**DL4**	0.262	0.919
SLA1	0.021^{*}	0.304	**FSW1**	0.001^{**}	0.383
SLA2	0.012^{*}	0.897	**FSW2**	0.020^{*}	0.897
SLA3	0.551	0.202	**FSW3**	0.119	0.192
SLA4	0.351	0.699	**FSW4**	0.870	0.252
H1	0.013^{*}	0.412	**DSW1**	0.005^{**}	0.730
H2	0.007^{**}	0.549	**DSW2**	0.006^{**}	0.789
H3	0.962	0.316	**DSW3**	0.294	0.292
H4	0.776	0.737	**DSW4**	0.863	0.094
FLW1	0.002^{**}	0.363	**DS1**	0.243	0.963
FLW2	0.005^{**}	0.774	**DS2**	0.000^{**}	0.050^{*}
FLW3	0.157	0.225	**DS3**	0.641	0.394
FLW4	0.780	0.026^{*}	**DS4**	0.199	0.581
DLW1	0.001^{**}	0.251	**FFW**	0.580	0.696
DLW2	0.000^{**}	0.854	**DFW**	0.718	0.973
DLW3	0.344	0.277	**DF**	0.143	0.004
DLW4	0.136	0.021		0.479	0.766
			HI	0.904	0.689

**. Significant at the 0.01 level
*. Significant at the 0.05 level

The correlations between all the measured parameters were calculated. DFW was the most important parameter to be estimated using the other measured parameters (Table 3).

From findings of the research (Fig. 1), DFW has significant correlations with FFW, E_w, and HI at the level 0.01, and with $SLA3^{-1}$, H3, FLW3, DLW3, FSW3, DSW3, and $DS1^{-1}$ at level 0.05. The regression equations were fitted between DFW and the correlated parameters (Figure 2). Modelling by AquaCrop

AquaCrop is a user friendly, accurate, robust and simple model needing a small number of input parameters (Patel et al, 2013) simulating the final crop yield as influenced by water availability and consumption, field management parameters, plant physiology, soil water and salt budgeting concepts (Vanuytrecht et al., 2014). These data were used as the model inputs and AquaCrop simulated the DFW (Table 4).

3- 2. Model evaluation

Based on the measured parameters, DFW was estimated by AquaCrop, as a mechanistic model. DFW was also predicted by regression equations (empirical model) (Table 4). Then the measured DFW was compared to the simulated DFW (Table 4).

The evaluation was accomplished using Normalized Root Mean Square Error (NRMSE) and Coefficient of Residuals (CRM) that are defined in Eqns. (8) and (9), respectively. NRMSE values less than 10% are ideal, while the values of 10% to 30% are also acceptable, and values more than 30% are not reliable (Bazaneh et al., 2016).

Table 3- Correlations between DFW with other parametrs.

		DFW			DFW			DFW			DFW
LAI1	**r**	.274	**H3**	**r**	.757*	**DL1**	**r**	-.126	**DSW3**	**r**	.669*
	S	.475		**S**	.018		**S**	.746		**S**	.049
LAI2	**r**	.023	**H4**	**r**	-.552	**DL2**	**r**	.048	**DSW4**	**r**	-.414
	S	.953		**S**	.123		**S**	.903		**S**	.269
LAI3	**r**	-.062	**FLW1**	**r**	.387	**DL3**	**r**	.357	**DS1**	**r**	-.680*
	S	.874		**S**	.303		**S**	.345		**S**	.044
LAI4	**r**	-.494	**FLW2**	**r**	.008	**DL4**	**r**	.108	**DS2**	**r**	-.172
	S	.176		**S**	.984		**S**	.783		**S**	.658
SLA1	**r**	-.509	**FLW3**	**r**	.689*	**FSW1**	**r**	.370	**DS3**	**r**	.630
	S	.162		**S**	.040		**S**	.326		**S**	.069
SLA2	**r**	-.129	**FLW4**	**r**	-.267	**FSW2**	**r**	-.053	**DS4**	**r**	.441
	S	.740		**S**	.488		**S**	.892		**S**	.234
SLA3	**r**	-.687*	**DLW1**	**r**	.386	**FSW3**	**r**	.674*	**FFW**	**r**	.924**
	S	.041		**S**	.305		**S**	.047		**S**	.000
SLA4	**r**	-.354	**DLW2**	**r**	.017	**FSW4**	**r**	-.617	**DF**	**r**	-.241
	S	.349		**S**	.964		**S**	.077		**S**	.532
H1	**r**	.510	**DLW3**	**r**	.716*	**DSW1**	**r**	.242		**r**	.872**
	S	.161		**S**	.030		**S**	.530		**S**	.002
H2	**r**	-.043	**DLW4**	**r**	-.227	**DSW2**	**r**	-.105	**HI**	**r**	.926**
	S	.912		**S**	.558		**S**	.788		**S**	.000

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

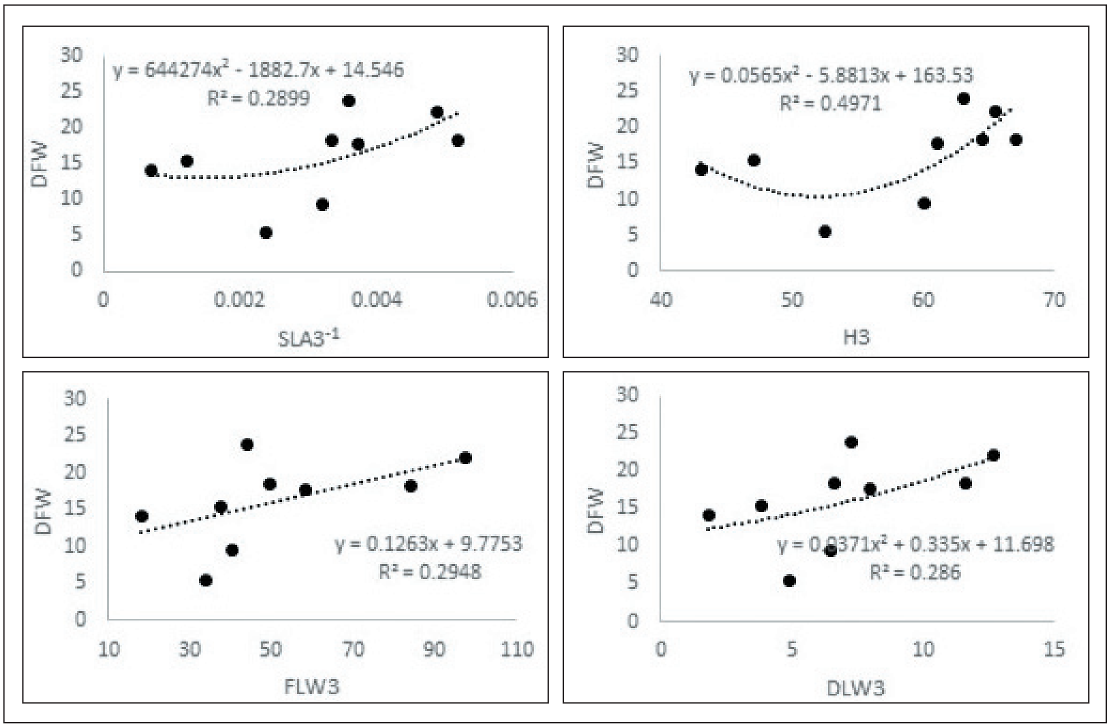

Fig. 2- Regression equations fitted for DFW.

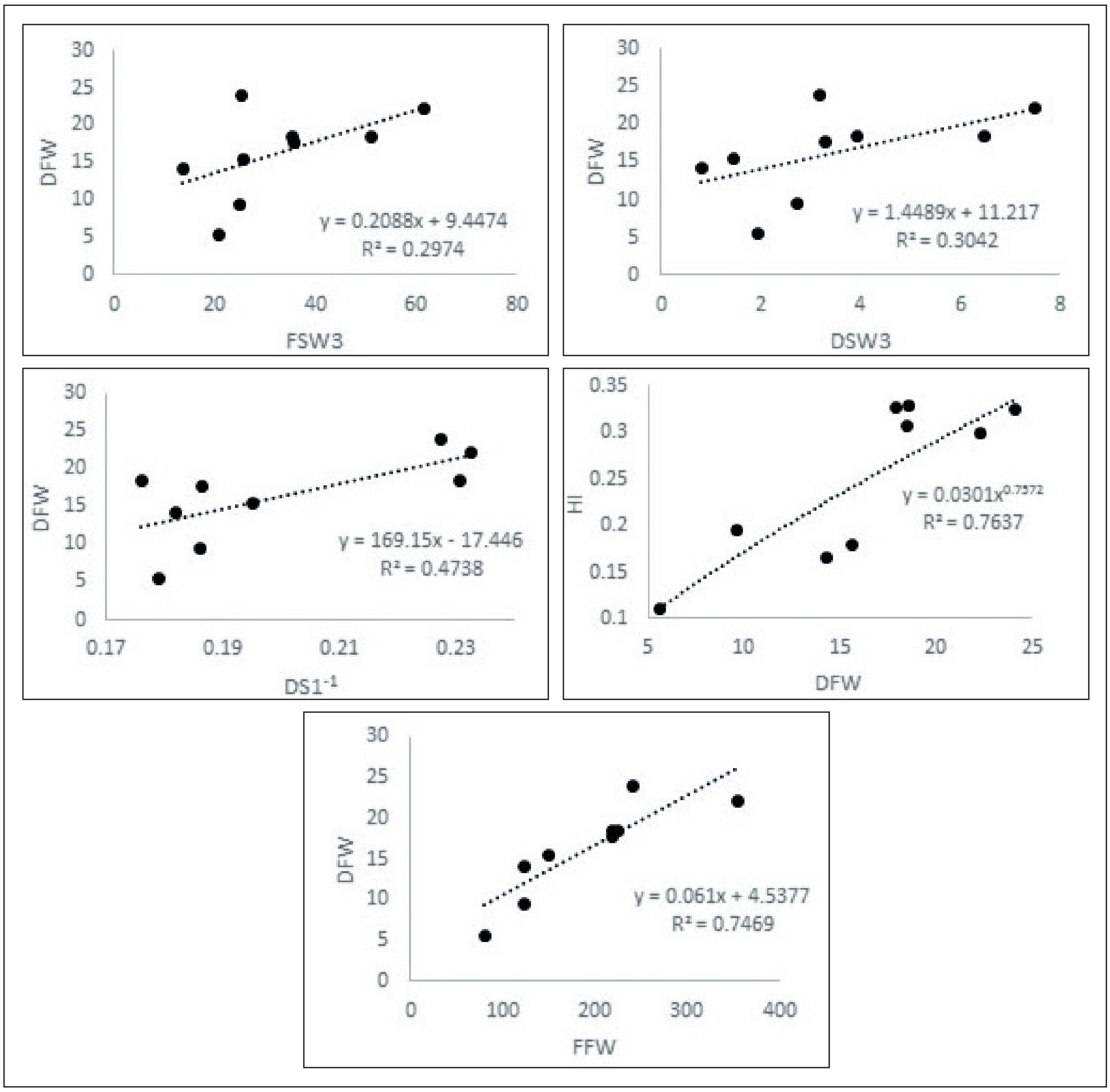

Fig. 2- Regression equations fitted for DFW.

$$NRMSE = \frac{100 \times \sqrt{\frac{\sum_1^n (M_i - S_i)^2}{n}}}{\frac{\sum_1^n M_i}{n}} \qquad (8$$

$$CRM = 1 - \frac{\sum_1^n S_i}{\sum_1^n M_i} \qquad (9$$

Where S_i is the simulated amount, M_i is the measured amount, and n is the number of samples.

As shown in Table 4, AquaCrop (ACs) could not simulate the tomato dry fruit weight well. On the other hand, the regression equations for predicting DFW based on $SLA3^{-1}$, H3, FLW3, DLW3, FSW3, DSW3, $DS1^{-1}$, and FFW were evaluated by NRMSE and CRM. It was found that these parameters are more reliable for predicting DFW. The minus CRM values represent the overestimation by the simulation model.

4- Discussion

The changing behavior of SLA (Figure 1) may be due to the plant development and the consequent changes in leaf properties (Van Iersel, 2003); however, the rate of leaves area enhancement was not the same as their weight increasing rate. It can be concluded that the leaf thickness was decreased during the periods when leaf area growth rate was more than leaf weight. As growth rate (that is the result of photosynthesis (Le Bot et al., 1998)) is also a function of leaf thickness (Niinemets, 1999). In the other words, dry matter accumulation would increase by leaf thickness augmentation.

Changing rates of biomass fresh/dry weight between the 45 DAP and 55 DAP (Fig. 1) may be due to normal variations in crop development (Steduto et al., 2012).

The irrigation effect was significant on some of tomato plant characteristics at the first and the second stages of sampling (33 and 45 DAP, respectively) (Fig. 1); however, the treatment had no significant effect of the measured and calculated characteristics in the next stages of sampling. In an other word, the effect of irrigation treatment on the overall performance of the studied tomatoes was compensated at the next stages and was ignorable.

Table 4- Acuracy of the simulated DFW values.

T	DFWm	DFWs								
		Acs	**1/SLA3**	**H3**	**FLW3**	**DLW3**	**FSW3**	**DSW3**	**1/DS1**	**FFW**
i11	18.51	107.13	13.55	23.11	15.99	15.92	16.84	16.89	12.30	19.19
i12	17.85	107.13	13.22	15.01	17.08	17.08	16.87	15.98	14.03	18.90
i13	14.23	107.13	13.70	15.10	12.06	11.61	12.31	12.41	13.25	11.38
i21	18.47	81.93	15.09	19.24	20.38	20.35	20.12	20.61	21.51	18.93
i22	22.28	81.93	15.40	20.70	22.07	21.28	22.27	22.04	21.86	20.38
i23	15.61	81.93	16.08	11.92	14.47	13.44	14.76	13.30	15.54	14.01
i31	9.59	53.01	16.42	14.05	14.86	15.74	14.60	15.17	13.97	11.37
i32	5.61	53.01	20.66	10.49	14.01	14.35	13.78	14.01	12.76	6.11
i33	24.08	53.01	20.66	17.26	15.29	16.44	14.67	15.82	21.00	19.91
Average	16.25	80.69	16.09	16.32	16.25	16.25	16.25	16.25	16.25	15.58
T		**NRMSE**								
		Acs	**1/SLA3**	**H3**	**FLW3**	**DLW3**	**FSW3**	**DSW3**	**1/DS1**	**FFW**
i11		181.82	145.05	9.44	5.17	5.32	3.43	3.32	12.74	1.39
i12		183.18	176.87	5.83	1.58	1.57	2.01	3.84	7.83	2.15
i13		190.61	1.26	1.79	4.45	5.37	3.94	3.74	2.01	5.84
i21		130.20	387.07	1.58	3.92	3.86	3.38	4.38	6.24	0.95
i22		122.39	336.81	3.23	0.43	2.06	0.03	0.49	0.87	3.90
i23		136.07	27.01	7.58	2.33	4.46	1.74	4.75	0.15	3.28
i31		89.10	116.55	9.16	10.82	12.64	10.30	11.46	8.99	3.66
i32		97.25	59.48	10.01	17.23	17.94	16.76	17.24	14.67	1.03
i33		59.37	178.55	13.99	18.01	15.66	19.30	16.94	6.31	8.54
Average		132.22	0.33	0.15	0.00	0.00	0.00	0.00	0.00	1.38
T		**CRM**								
		Acs	**1/SLA3**	**H3**	**FLW3**	**DLW3**	**FSW3**	**DSW3**	**1/DS1**	**FFW**
i11		-4.79	3.82	-0.25	0.14	0.14	0.09	0.09	0.34	-0.04
i12		-5.00	4.83	0.16	0.04	0.04	0.05	0.10	0.21	-0.06
i13		-6.53	-0.04	-0.06	0.15	0.18	0.14	0.13	0.07	0.20
i21		-3.44	10.21	-0.04	-0.10	-0.10	-0.09	-0.12	-0.16	-0.03
i22		-2.68	7.37	0.07	0.01	0.04	0.00	0.01	0.02	0.09
i23		-4.25	0.84	0.24	0.07	0.14	0.05	0.15	0.00	0.10
i31		-4.53	5.93	-0.47	-0.55	-0.64	-0.52	-0.58	-0.46	-0.19
i32		-8.45	5.17	-0.87	-1.50	-1.56	-1.46	-1.50	-1.27	-0.09
i33		-1.20	3.61	0.28	0.36	0.32	0.39	0.34	0.13	0.17
Average		-3.97	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.04

As a main result of this research, it can be deduced that phenologic characteristics of plants at the 3rd stage of sampling was more efficient in predicting the yield of studied tomatoes. In other words, the DFW can be estimated by specific leaf area, plant height, fresh leaf weight, dry leaf weight, fresh stem weight, and dry stem weight when the tomato plants are in mid-life (flowering stage of development).

In this research, proportional stem dry matter in the vegetative stage (likely during the first third of plant life time) was found to have a significant effect on predicting the tomato yield; however, it needs more investigation to approve or reject the result.

As a whole, flowering stage of studied tomatoes has a significant effect on plant yield. Therefore, more investigation needs to be carried out to find the best treatment for enhancing tomato productivity at this stage of growth and development.

5- Conclusions

An empirical model was developed here to predict tomato yields based on phenologic characteristics. Therefore, the crop was cultivated under controlled conditions with different irrigation treatments and their phenologic characteristics have been measured in four stages.

The irrigation treatment has significant effect on LAI1, LAI2, H2, FLW1, FLW2, DLW1, DLW2, DL2, FSW1, DSW1, DSW2, and DS2 at the level 0.01, while its effect on SLA1, SLA2, H1, and FSW2 is significant at the level 0.05. These significant effects were observed at the first (33 DAP) and the second (45 DAP) sampling stages and compensated at the next stages of development.

Dry fruit weight correlation with other parameters was developed. DFW has significant correlations with FFW, E_w, and HI at the level 0.01, and with $SLA3^{-1}$, H3, FLW3, DLW3, FSW3, DSW, and $DS1^{-1}$ at the 0.05 level.

The regression equations between given and correlated parameters were developed and the models were evaluated. It was found that phenologic characteristics of tomato (‘Early Ch.’) measured at the mid-life (flowering stage) have the most significant effect on plant production, i.e. tomato yield, water efficiency and harvest index can be estimated when the flowering stage of plant development occurs.

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