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Growth regularities and dry organic biomass accumulation rates in drip-irrigated tomato under different soil watering thresholds

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ABSTRACT

This study established the regularities of dry organic matter accumulation throughout the growth period of drip-irrigated tomato (*Solanum lycopersicum* L.), cultivated in the cold semi-arid climate zone (BSk), under various watering thresholds using a logistic function. The proposed mathematical models closely matched the empirical data, yielding strong coefficients of determination (R^2 of 0.98). Growth parameter modeling demonstrated that maintaining a soil moisture threshold in the layer 0–50 cm of at least 70% field capacity (FC) from seedlings planting to budding, followed by 80% FC during peak growth intensity, optimizes biomass accumulation dynamics. The absolute highest dry organic matter accumulation rate (0.623 t ha^{-1} day^{-1}) was recorded at the critical curve inflection point (T_2) under a dynamic 70–80–70% FC irrigation regime. Peak growth acceleration (0.024 t ha^{-1} day^{-2}) occurred at critical point T_1. The intensive growth phase terminated upon reaching critical point T_3, transitioning into a deceleration phase characterized by negative acceleration values, which temporally coincided with intensive fruit formation. The duration of this intensive growth window varied from 13.2 to 19.1 days depending on moisture availability. Ultimately, maintaining soil moisture below 70% FC or exceeding 80% FC is agronomically impractical because these moisture extremes significantly depress both growth rate and acceleration, reducing overall crop productivity.

Keywords: critical stage, growth rates, irrigation, logistic function, mathematical modeling, watering threshold.

INTRODUCTION

Tomato (*Solanum lycopersicum* L.) is among the most commercially important vegetable plants worldwide. According to current statistical data, tomato occupies second place, after potato, in total non-starchy vegetable production. It would be no exaggeration to consider the tomato the most globally produced and consumed fresh-market vegetable (Padmanabhan et al., 2016). Annual tomato production reaches 180–200 million metric tons, with an estimated global gross fruit value of about 100 billion USD (Maurya et al., 2025). Considering its huge economic value, it is natural that the tomato is among the vegetables of greatest interest and popularity among farmers engaged in vegetable production. Every year, new hybrids with better qualities and productivity are created by plant breeding companies; each year, new valuable investigations are conducted to improve crop cultivation technology through better utilization of natural resources, improved pest and disease control, harvesting and post-harvest processing, etc. Regarding agrotechnological interventions, irrigation is among the most influential factors of tomato productivity, especially in regions with initially insufficient and unstable natural moisture supply. Therefore, current agricultural science is working to develop novel irrigation methods and improve existing ones to ensure the highest tomato fruit output per unit of irrigation water, optimal economic efficiency, preservation of freshwater resources, and environmental safety (Mukherjee et al., 2023).

Irrigation significantly improves tomato growth and development, especially in arid and semi-arid regions with risky agriculture. However, the strength of the effect and the best options for artificial water supply differ depending on the genetic features of the cultivated crop hybrids and soil-climatic conditions. Most studies report that the best outcomes are achieved by maintaining 80–100% of the crop evapotranspiration (ETc) irrigation rate. For example, Etissa et al. (2014) determined that full irrigation (100% ETc) produced the maximum yield (82.14 t/ha) compared to 80% ETc (57.30 t/ha) and 60% ETc (49.30 t/ha) options. The main drawback of using ETc as a reference for irrigation rate evaluation and timing is that tomato evapotranspiration rates will differ depending on the method of ETc evaluation; besides, using non-calibrated crop coefficient values for the stages of growth and development will become a source of additional miscalculation and erroneous estimation of the crop's water demands (Vozhehova et al., 2018).

However, not all studies focus on ETc-based irrigation of tomato. Owusu-Sekyere and Dadzie (2010) reported the best growth, development, and productivity of tomato at 80% of the lowest field capacity (FC) under differentiated scheduling of water supply depending on the crop's growth stages.

As for irrigation frequency, Bar-Yosef et al. (1980) demonstrated that increasing frequency from one to three times daily significantly increased dry matter output, which was mainly achieved at the expense of better plant root development. Monte et al. (2009) recommend irrigating every two days, while Saha and Hara (1998) claimed that the best results in tomato cultivation were achieved under a flexible schedule and watering when soil moisture content is depleted by 15%. In general, drip irrigation at 80% FC is frequently quoted as optimal across numerous studies; however, some discrepancies in timing and critical stages of watering remain the subject of scientific debate and are strongly dependent on the environmental conditions of tomato cultivation, as well as the irrigation machinery and plant genotypes used in production (Nurzoda, 2024).

Another interesting fact is that in some cases, subtle water stress under controlled irrigation can be beneficial for yield quality and result in larger fruit and higher sugar, lycopene, and β-carotene content in the products (Lipan et al., 2021). However, farmers must be extremely cautious when creating artificial water stress for tomato, as in the case of a mistake, they risk facing heavy yield losses, because it is a well-established fact that tomato yields tend to decrease dramatically under water deficit. The greatest losses are associated with water deficit at the critical stages of crop growth and development. In some cases, losses can amount to almost 65% of projected yields (Durdu et al., 2024).

And lastly, the question of ceasing watering on time is another important problem worthy of attention. The common practice is to decrease irrigation intensity or even cease watering when tomato growth slows down. Overwatering at the time of decelerated vegetative growth results in unproductive irrigation water losses and prolongs the period of crop vegetation, which leads to yield quality deterioration due to fruit cracking and splitting, root and blossom rot, fungal diseases, and waterlogging. Besides, dry matter and sugar content in fruit tend to decrease in this case (Cahn et al., 2003).

To avoid the mentioned consequences, it is essential to determine the beginning and end of intensive vegetative growth and the duration of critical periods of the crop in order to make reasonable decisions about starting and finishing irrigation, as well as to calculate watering rates and frequency. Based on domestic and international scientific experience, these problems are usually solved through mathematical modeling of crop growth processes using Gompertz and Richardson , or logistic curve function (Karadavut et al., 2010; Hunt, 2012). The logistic function is used to solve questions related to the determination of plant growth because it is continuous, differentiable at every point, and has an inflection point that makes the plot symmetric (Ismail, 2005). Besides, the Gompertz logistic curve function is only slightly inferior in plant growth modeling to more complex and computationally demanding models based on ensemble machine learning algorithms, such as XGBoost or LightGBM, while simultaneously providing better interpretability and transparency compared to ML-driven approaches (Gachoki et al., 2002). Critical points on the growth curves can be mathematically calculated using the approximation function. For example, Gregorczyk (1998) worked with the Richards function and observed three critical points of crop growth: the inflection point and the minimum and maximum acceleration points. The logistic regression function was implemented in recent research on the effects of irrigation deficit on grain corn growth and development (Hocaoğlu et al., 2023). Sepaskhak et al. (2011) implemented the logistic function to quantify the impact of water and nitrogen application rates on grain corn biomass accumulation and yield. As for tomato, Baar et al. (2024) recently implemented a logistic model to provide long- and short-term prediction of fruit size, yield, and general crop growth estimation.

Notwithstanding the widespread use of logistic functions in crop growth models, there is still a gap in studies related to logistic modeling of tomato dry matter accumulation depending on irrigation. Therefore, the main hypothesis of the current study is that the logistic curve can precisely describe the process of dry matter accumulation in the tomato plant.

The goal of the study is to evaluate the intensity of dry matter accumulation in tomato plants under different irrigation schedules, based on prewatering levels of soil moisture, and to determine the model's parameters, speed, and acceleration of plant growth, and the beginning, end, and duration of critical periods in order to establish the optimal growth parameters by the stages of crop development.

MATERIALS AND METHODS

Study design and experimental methodology

Field experiments were conducted from 2019 to 2021 at the Agro-Liga Private Enterprise, located in Chaplynka, Kakhovka district, Kherson region. The precise geographic coordinates of the experimental fields for each growing season were as follows: 2019 – 46°22'55.7"N 33°22'15.7"E; 2020 – 46°23'33.3"N 33°22'24.0"E; 2021 – 46°25'57.1"N 33°24'59"E.

Climatologically, the study area is situated within the Dry Steppe zone of Ukraine, corresponding to a semi-arid cold climate (BSk) according to the Köppen-Geiger classification system, characterized by moderately hot and semi-arid conditions (Peel et al., 2007).

The soil at the experimental site is classified as a dark-chestnut, slightly saline, residually sodic soil. The content of physical clay in the soil layer 0-50 cm fluctuated within 48–56%. The bulk density of the soil layer 0–50 cm was 1.45 g cm^{-3}. The field capacity of the 0–50 cm layer was 25.8% from the absolutely dry soil weight. The soil layer 0–50 cm contained 65 mg kg^{-1} of total nitrogen, 53 mg kg^{-1} of mobile phosphorus, and 457 mg kg^{-1} of exchangeable potassium, respectively.

The tomato hybrid Melman F1 for the fresh food market was cultivated via seedling transplantation. The agricultural practices followed common regional guidelines for irrigated tomato production in the Dry Steppe zone of Ukraine. Complex fertilization system included local application of $N_6P_{26}K_{30}$ at the time of transplantation with further fertigation $N_{120}P_{45}K_{90}$ and foliar treatment with Humifield (3 times per growing season, 0.1 L ha^{-1}), Nutrivant Plus "Solanaceous" (2 times per growing season, 2.0 L ha^{-1}), Microcat Calcium (1.0 L ha^{-1} once per growing season), and Microcat Boron (1.0 L ha^{-1} once per growing season). Seedlings were planted using a Ferrari F-MAX-3 planter with a row-to-plant spacing configuration of 1.5 × 0.20 m. Planting was executed between May 3 and May 15 each year, depending on prevailing weather conditions. Plant care was common for irrigated tomato cultivation. As for plant protection, the following system of integrative pesticide usage was applied:

- Herbicides.

Roundup, SL (glyphosate, 4 L ha^{-1}) was applied after harvesting the previous crop in the presence of actively growing perennial (root-sprouting) weeds. Stomp 330, EC (pendimethalin, 4 L ha^{-1}) was applied before planting.

- Fungicides

Fungicide treatments were initiated at the first onset of visual disease symptoms and repeated at 10-day intervals depending on weather conditions. The applications were rotated between the following products: Quadris 250, SC (azoxystrobin, 3 treatments at a rate of 0.6 L ha^{-1}); Ridomil Gold MZ 68, WG (metalaxyl-M + mancozeb, 3 treatments at a rate of 2.5 kg ha^{-1}).

- Insecticides – were applied when pest populations exceeded the levels of economic threat to harvest, and included the following preparations: Decis Profi 25, WG (deltamethrin, at a rate of 0.05 kg ha^{-1}); Actellic 500, EC (pirimiphos-methyl, at a rate of 1.5 L ha^{-1}).

The study was performed in four replications using a systematic design. The field trials evaluated seven distinct pre-irrigation soil moisture thresholds (active watering layer was 0-50 cm throughout the whole growing season of tomato) based on field capacity (FC):

- Watering at the root only with no further irrigation;
- Watering upon reaching the watering threshold of 60% FC;
- Watering at 70–80–70% FC dynamic threshold for "planting–budding" – "budding–fruit formation" – "fruit formation–ripening", respectively;
- Watering at 80% FC threshold;
- Watering at 80–85–80% FC dynamic threshold for "planting–budding" – "budding–fruit formation" – "fruit formation–ripening", respectively;
- Watering at 90% FC threshold;
- Watering at 100% FC threshold (continuous irrigation without interruption, soil was kept continuously saturated with moisture).

Water was applied via a drip irrigation system sourced from the Chaplynka main irrigation canal. Netafim Streamline 80 drip tape was used in the trials. The wall of the tape was 0.2 mm thick; the distance between emitters was 30 cm, the working pressure was 0.055 MPa, and the water discharge was 1.05 L $hour^{-1}$. The irrigation water was classified as marginally suitable for agricultural use due to high alkalinity (pH ranging from 7.6 to 8.1). The water chemical profile exhibited total mineralization of 0.44–0.55 g L^{-1}, bicarbonates concentration was 0.17–0.18 g L^{-1}, magnesium – 0.05–0.06 mg L^{-1}, calcium – 0.04–0.05 mg L^{-1}, sodium and potassium – 0.02–0.03 mg L^{-1}, respectively.

Soil moisture dynamics were continuously monitored using in-field Watermark 200SS sensors integrated with an iMetos® IMT 300 weather station. The sensors were calibrated throughout the tomato growing season using the gravimetric method across four replications per variant. For calibration, gravimetric soil core samples were collected at 10-cm increments down to a depth of 50 cm and oven-dried at 105 °C until a constant mass was achieved (Rasheed et al., 2022). To evaluate crop biomass parameters, the dry organic matter of the tomato aboveground biomass was determined refractometrically from composite samples consisting of 20 representative plants through drying the vegetative biomass of the plant to 0% of moisture content in the plant tissues (Stoyanova et al., 2018). The yield was harvested using Mark One S.r.l. self-propelled tomato harvester.

Mathematical modeling

Because the empirical accumulation curves of dry organic matter exhibited a non-linear, asymmetric progression, a three-parameter logistic function was selected to characterize the growth kinetics. Dry matter accumulation as a function of the watering thresholds was modeled using the following logistic equation, Equation 1:

$$Y = \frac{A}{1 + 10^{a+bx}} \tag{1}$$

where: Y is a calculated dry matter yield, t ha^{-1}; A is the difference between the higher and lower asymptotes of dry matter yield, t ha^{-1}; x is the duration of growing season, days; a and b are the constants that determine the slope and inflection characteristics of the curve.

The constants a and b for each equation were estimated using the ordinary least squares (OLS) method and were further used to determine the theoretical dry biomass of tomato plants (y_t). The growth speed rate and acceleration at any point of the logistic curve were calculated as the first Equation 2 and second Equation 3 derivatives of the function, respectively:

$$y' = 2.302|b|y_t(1 - \frac{y_t}{A}) \tag{2}$$

$$y'' = 2.302|b|y'(1 - \frac{2y_t}{A}) \tag{3}$$

The coordinates of the inflection point T_2, which characterizes the transition from increasing to decreasing dry matter accumulation, were calculated as follows, Equations 4, 5:

$$\bar{x} = \frac{a}{|b|} \tag{4}$$

$$\bar{y} = 0.5A \tag{5}$$

The ordinates of points T_1 and T_3 that correspond to the beginning and end of the intensive growth were evaluated using formulas Equations 6, 7. The corresponding ordinates on the growth speed rate curve were calculated using formula Equation 8, while those on the acceleration curve were calculated using formulas Equations 9, 10.

$$\bar{y}_1 = 0.2113A \quad (6)$$

$$\bar{y}_2 = 0.7887A \quad (7)$$

$$\bar{y}'_{1,2} = 0.3838Ab \quad (8)$$

$$\bar{y}''_1 = 0.05102Ab^2 \quad (9)$$

$$\bar{y}''_2 = -0.05102Ab^2 \quad (10)$$

The abscissae of points T_1 and T_3 on the growth curve were calculated using formula Equation 11:

$$\bar{x}_{1,2} = \bar{x} \pm \frac{0.5719}{b} \quad (11)$$

The duration of the critical growth stage was determined using formula Equation 12:

$$\varphi = \frac{1.1438}{|b|} \quad (12)$$

The goodness-of-fit and approximation capacity of the logistic models were evaluated using the coefficient of determination (R^2) in accordance with standard statistical procedures of Pearson's correlation analysis (Mundu et al., 2026). Mathematical simulations and parameter optimizations were performed at a 95% confidence interval. To distinguish the among the studied variants, one-way ANOVA with replications was performed at 95% confidence interval ($p < 0.05$) using Fisher's criterion. Data processing and visualizations were performed in Python 3.10 using libraries NumPy, Pandas, Statsmodels, SciPy, Matplotlib, Seaborn (Wang et al., 2022).

RESULTS

The present study established the primary regularities governing dry organic matter accumulation (a direct indicator of tomato productivity), alongside key crop growth and development characteristics across various irrigation schedules. The empirical data indicate that dry organic matter yield significantly depends on the watering threshold. Notably, both insufficient and excessive moisture supply suppressed dry organic matter accumulation in tomato plants. Because crop productivity is inherently derived from growth intensity, a detailed logistic function analysis was performed to evaluate how different watering thresholds influence tomato growth dynamics. Consequently, the parameters of the growth processes were modeled from the date of seedling transplantation to the onset and termination of the intensive growth phase (corresponding to critical points T_1 and T_3). Furthermore, the maximum rate and acceleration of dry organic matter accumulation were determined relative to the watering thresholds during this growing period. Specifically, the first critical growth phase (T_1), where the acceleration of dry organic matter accumulation reaches its maximum, occurred 39.5 days after transplantation under the 100% field capacity (FC) irrigation regime. This onset was 1.3 to 2.4 days earlier than in the other experimental variants. The second critical growth phase (inflection point T_2), at which the dry matter yield reaches half of its potential maximum, occurred at 47.7 days in the rooting-only watering variant and at 49.0 days in the 100% FC variant (Table 1).

Comparing the coordinates at point T_2 demonstrates that lower watering thresholds shortened the duration of the growth period prior to this critical point to a maximum of 47.7 days. Conversely, under the 100% FC regime, this period extended to 49.0 days. This shifts the timeline of the maximum growth acceleration rate depending on moisture availability. In the non-irrigated variant, the rate of dry matter accumulation peaked at 0.27 t ha^{-1} day^{-1} at 47.7 days post-transplantation. Increasing the watering threshold to 60% FC elevated the peak accumulation rate to 0.43 t ha^{-1} day^{-1}. The highest accumulation rate of 0.65 t ha^{-1} day^{-1} was achieved under the dynamic, differentiated 70–80–70% FC threshold after 48.4 days. This fact could be attributed to the biological requirements of the tomato plant at different growing stages. Differentiation of this kind provided the best optimization of soil moisture regime, resulting in the best root growth conditions that led to the best outcomes in dry matter yield. For all remaining variants, excluding the 100% FC treatment, the accumulation rate at the critical point T_2 converged between 0.57 and 0.60 t ha^{-1} day^{-1} at 48.7 to 48.9 days after transplantation. Finally, the ordinates of the logistic curves confirm that soil moisture conditions above 80% FC are

Table 1. Parameters of logistic functions, yields of dry organic matter, and coordinates of inflection points at different watering thresholds

Watering threshold, % FC	Y_{max}, t ha^{-1}	Y'_{max}, t ha^{-1}	Parameters of the logistic function		Coordinates of T_2 point	
			a	*b*	$\bar{x}$, days	$\bar{y}$, t ha^{-1}
Without irrigation (watering at the root only)	6.76^a	6.74^a	3.287244	-0.06895	47.7	3.37
60	8.71^b	8.69^b	4.099669	-0.0861	47.6	4.35
70-80-70	11.70^c	11.69^c	3.979381	-0.08227	48.4	5.85
80	13.92^d	13.91^d	3.484413	-0.07119	48.9	6.95
80-85-80	14.10^e	14.09^e	3.560768	-0.07319	48.7	7.05
90	13.09^f	13.08^f	3.459496	-0.07071	48.9	6.54
100	11.37^g	11.39^g	2.9392	-0.05994	49.0	5.69

Note: T_1, T_2, and T_3 denote critical physiological milestones on the logistic growth curve, representing the onset of intensive growth (maximum acceleration), the inflection point (half-maximum dry matter accumulation), and the termination of intensive growth, respectively. Different superscript letters mean significant difference between the variants at $p < 0.05$ in accordance with ANOVA results.

substantially more favorable for dry organic matter accumulation, as evidenced by the peak yield range of 6.95 to 7.05 t ha^{-1}.

Based on empirical dry organic matter yields obtained under various irrigation regimes, logistic functions were developed to model the primary parameters of tomato growth . Because the logistic function is twice-differentiable, it allowed for the precise determination of both the maximum growth rate (occurring at the inflection point, T_2) and the peak growth acceleration (occurring at the transition point, T_1). Across all treatments, the maximum growth rates at point T_2 spanned from 0.256 to 0.623 t ha^{-1} day^{-1}, with the highest rates concentrated within the 0.553–0.623 t ha^{-1} day^{-1} range for the optimal and dynamic irrigation treatments (Table 2). Concurrently, the peak growth acceleration of biomass accumulation across the variants ranged between 0.001 and 0.024 t ha^{-1} day^{-2}. The exceptionally high coefficients of determination (R^2 of 0.978) demonstrate that the proposed logistic equations possess strong predictive power and accurately reflect the actual dynamics of tomato vegetative development. (Table 2).

The presented logistic curves accurately reflect the duration of critical growth phases across the different watering thresholds throughout the vegetative period of tomato (Figure 1).

Calculations of the growth duration up to the critical point T_3 indicated that the intensive growth phase concludes at 54.3 days post-transplantation under the 60% FC irrigation regime. In the non-irrigated (watering at rooting only) variant, the transition to the growth inhibition phase occurred after 55.9 days, marked by a decline in the dry matter accumulation rate to 0.18 t ha^{-1} day^{-1}. Upon reaching critical point T_3, the dry organic matter accumulation rate across all treatments decreased by nearly 1.5-fold compared to the peak values observed at the inflection point T_2 (Figure 2).

Table 2. Logistic function equations and peak kinetic growth parameters (maximum rate at T_2 and peak acceleration at T_1) under different watering thresholds

Watering threshold, % FC	Function equation	R^2	Maximum growth rate, t day^{-1}	Peak growth acceleration, t day^{-2}
Without irrigation (watering at rooting only)	$Y = 6.74 \times (1+10^{a+bx})^{-1}$	0.987	0.256	0.001
60	$Y = 8.75 \times (1+10^{a+bx})^{-1}$	0.978	0.413	0.017
70-80-70	$Y = 11.79 \times (1+10^{a+bx})^{-1}$	0.986	0.623	0.024
80	$Y = 12.23 \times (1+10^{a+bx})^{-1}$	0.987	0.569	0.021
80-85-80	$Y = 14.10 \times (1+10^{a+bx})^{-1}$	0.988	0.568	0.020
90	$Y = 13.08 \times (1+10^{a+bx})^{-1}$	0.985	0.553	0.019
100	$Y = 11.38 \times (1+10^{a+bx})^{-1}$	0.983	0.375	0.001

Note: For *a* and *b* coefficients, please, refer to the corresponding models from Table 1.

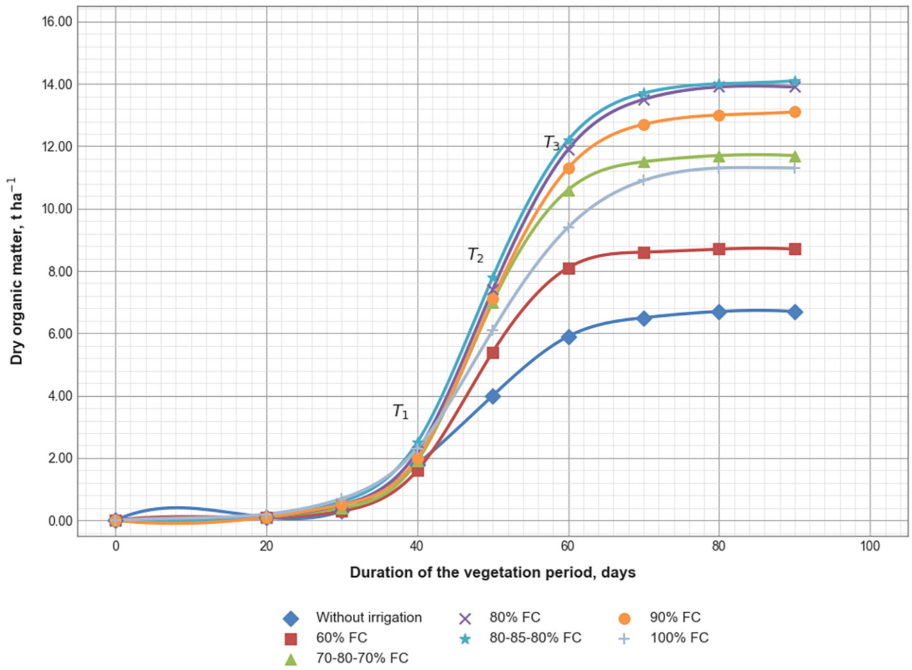

Figure 1. Dynamics of dry organic matter yield in tomato plants under different watering thresholds, approximated by a logistic function, t ha^{-1}

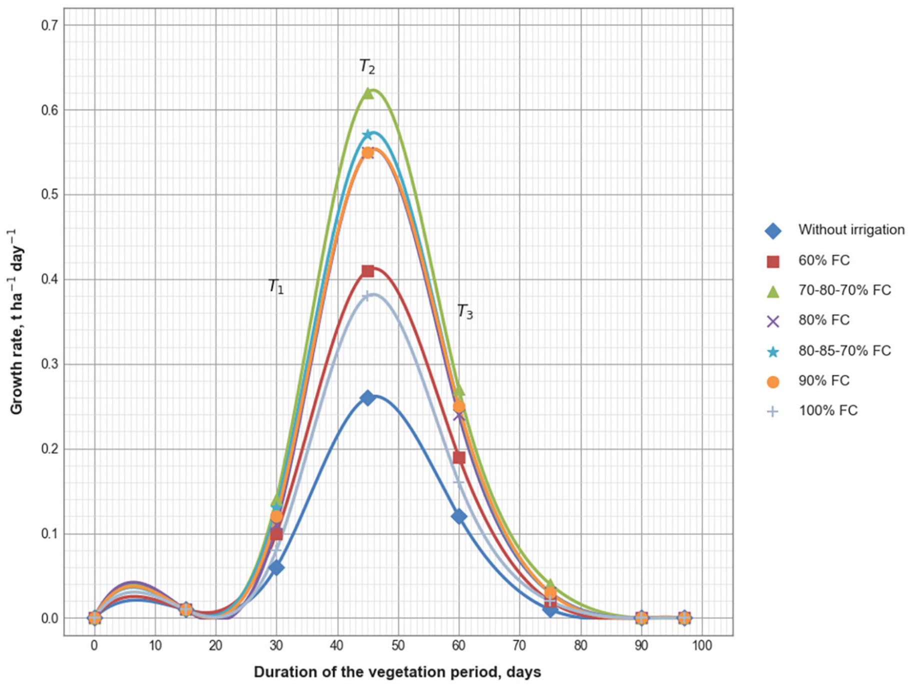

Figure 2. The rate of accumulation of dry mass of tomato plants under different watering thresholds, t ha^{-1}day^{-1}

Evaluating acceleration across these critical growth stages confirms that peak acceleration and maximum growth rate do not coincide temporally. While the maximum growth rate occurs at the inflection point (T_2), peak growth acceleration is achieved earlier, at the first critical point (T_1). Specifically, a maximum acceleration of 0.024 t ha^{-1} day^{-2} was reached 41.4 days after transplantation under the dynamic 70–80–70% FC watering threshold. Conversely, the lowest acceleration at T_1 was recorded in the rooting-only treatment, which was 66.7% lower than the dynamic 70–80–70% FC variant. Furthermore, increasing the watering thresholds to 80% and 90% FC suppressed plant growth acceleration by 25.2% compared to the optimal 70–80–70% FC regime.

As mathematically predicted by the logistic model, growth acceleration reaches zero at point T_2 (approximately 50 days post-transplantation) across all treatments, signifying the transition toward growth deceleration. Beyond this point, at critical stage T_3, growth acceleration values become negative for all evaluated watering thresholds. This negative acceleration strongly indicates a physiological shift in sink-source dynamics, reflecting the redistribution of photo-assimilates from vegetative structures toward reproductive organs during the intensive fruit-formation period (observed around day 60) (Figure 3).

The calculations of critical growth-phase durations revealed that the shortest intensive growth window occurred under the 60% FC threshold (13.2 days). Deviations from this threshold in any direction extended the duration of this critical window by 0.2 to 5.9 days. The longest critical phase duration was recorded under the 100% FC regime, lasting 19.1 days. Comparing these temporal intervals demonstrates that maintaining soil moisture at 100% FC is agronomically counterproductive. It not only significantly protracts the critical growth period but also reduces overall growth intensity, as validated by both the lowered accumulation rates and the diminished final dry organic matter yields.

DISCUSSION

Tomato dry matter yield modeling in dependence on different agrotechnological interventions is crucial both for a deeper theoretical understanding of plant reaction to anthropogenic inputs and better crop management decisions in practice. Currently, various modeling approaches are applied to this task. The choice of modeling algorithm depends on purpose, dataset size and quality, technical means and available computation power, level of scientific expertise, and target audience. In general, most modern models of tomato dry matter accumulation and yield could be subdivided into pure mathematical models (like those presented in the current study), dynamic simulation models (e.g., TOMSIM and TOMGRO), and machine/deep learning models (Higashide, 2022). Considering the inputs used to predict dry matter yield, models frequently utilize such variables as light-use efficiency, carbon dioxide levels, and air temperature as environmental parameters, and sowing/planting terms, plant density, cultivars, etc., as agrotechnological determinants of tomato growth and development (Wang et al., 2012; Saito et al., 2020). Also, remote sensing data has become increasingly important for tomato biomass accumulation estimation nowadays, especially

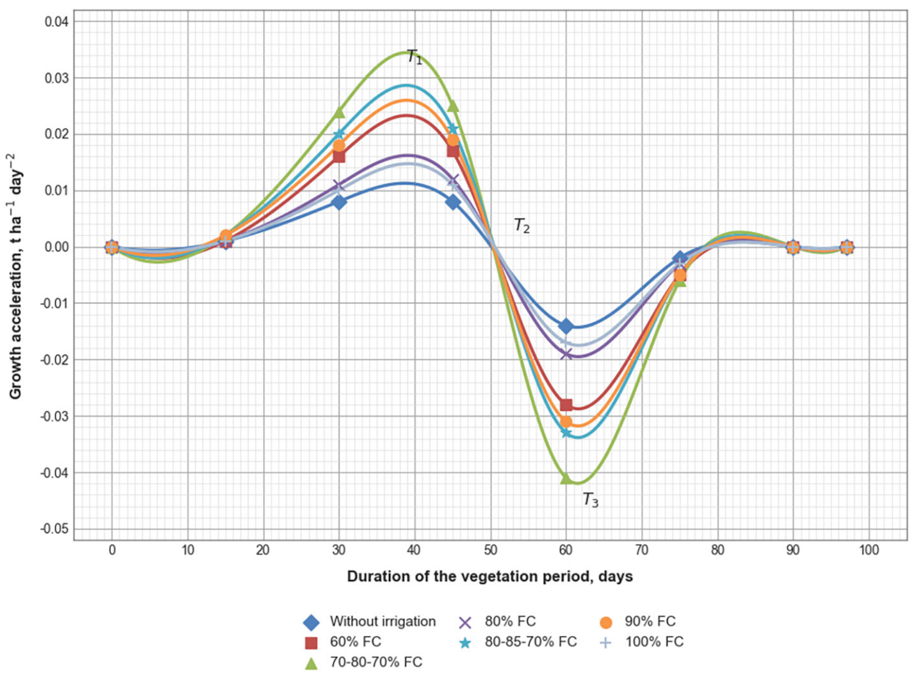

Figure 3. Acceleration of dry organic mass accumulation of tomato under different watering thresholds, t ha^{-1}day^{-2}

within the framework of complex architectures like ensemble learning models (Johansen et al., 2020). However, despite recent advances in tomato growth modeling, challenges remain regarding model generalizability across different environments, the need for extensive calibration, estimation of different agrotechnological impacts and their interaction on plant growth peculiarities, as well as the integration of physiological understanding with data-driven modeling approaches (Peng et al., 2023).

It should be noted that traditional mathematical functions are rarely applied to tomato dry matter predictions. Although empirical growth curves (e.g., Gompertz or logistic function) are also used for trait-specific predictions, such as stem or fruit dry weight of tomato (Fang et al., 2022), most researchers focus on a more complicated fusion of modeling algorithms, like the combination of mechanistic crop growth simulation models with machine/deep learning algorithms. For example, stacking ensemble models using simulated daily dry matter yields as additional features significantly improved prediction accuracy over standalone machine learning-based tomato models (Wang et al., 2024). Of course, hybrid approaches combining crop simulation outputs with machine learning improve prediction accuracy (Gong et al., 2021), but at the expense of transparency and interpretability. It is well known that most machine learning and deep learning models have a "black box" nature. Therefore, despite their excellent prediction accuracy and precise fitting ability, it is often impossible to explain why a model produces a particular output from a given set of inputs. This limitation makes such models less suitable for deeper theoretical investigation of the effects of agrotechnological interventions on crop growth and productivity. In contrast, mathematical models, such as the logistic function used in the present study, may be slightly inferior in predictive accuracy, but they offer greater practicality, universality, and interpretability (Rudin, 2019).

The logistic function is used to simulate the accumulation of dry matter in tomato crops, providing a biologically meaningful and mathematically interpretable approach to describe growth dynamics. Recent studies have demonstrated that logistic sigmoid models, despite their flaws, can accurately predict key growth traits such as plant height, leaf area index, photosynthetic activity, and dry biomass accumulation in greenhouse tomatoes (Gang et al., 2007; Fang et al., 2022). It should also be stressed that dynamic mathematical growth simulation models in decision support systems increasingly incorporate logistic-based sub-models to optimize irrigation, nutrient management, and yield prediction of tomato, making our approach practically valuable for precision digital agriculture systems (Carmassi et al., 2025). In addition, logistic sigmoid functions provide high-quality fit and capture critical phenological events in tomato the best (Gallardo et al., 2021).

Another point worth considering is that most described in recent academic literature on tomato growth and dry matter yield models were developed and calibrated for greenhouse conditions, and the adopted model stands alone as an open-field tomato model. In addition, the developed models contribute not only to the subject of dry matter yield predictions but also answer the questions of critical stages and growth patterns of tomato depending on irrigation scheduling. Recent models indicated that tomato yield is proportional to water reduction under deficit irrigation strategies (Badr et al., 2026) and relates cumulative temperature to aboveground biomass of tomato under different evapotranspiration fractions (100%, 75%, 50%), capturing how deficit irrigation alters dry matter output (Wu et al., 2021). Cobb-Douglas production function quantified elasticities as the following regulation: a 1% increase in irrigation increased dry matter yield of tomato by roughly 18% but reduced water-use efficiency of the crop; dry matter yield had a quadratic relationship with the crop photosynthesis depending on irrigation rates and schedule (Zhang et al., 2022). The importance of our logistic models lies not only in their ability to fit dry matter accumulation curves, but also in their capacity to transform growth dynamics into practical irrigation decisions. By identifying watering thresholds for the three major stages of tomato growth, these models make it possible to determine when drip irrigation should be intensified, reduced, or ceased to achieve the highest dry matter accumulation rate and final output. Thus, the obtained results are not limited to theoretical growth description; they provide interpretable and agronomically meaningful criteria for differentiated irrigation management.

CONCLUSIONS

Logistic modeling of dry organic matter accumulation in drip-irrigated tomato demonstrated that vegetative and reproductive dynamics in semi-arid cold climate zone at dark-chestnut slightly saline soil are heavily governed by irrigation scheduling. While the absolute highest growth rate (0.623 t ha^{-1} day^{-1}) was achieved under a dynamic 70–80–70% FC regime, the maximum dry organic matter yield (14.1 t ha^{-1}) was optimized under the dynamic 80–85–80% FC threshold. Continuous irrigation at 100% FC provides no benefits and results in a clear decline in crop growth. To secure high growth acceleration and rapid biomass accumulation during the critical first 40 days post-transplantation, maintaining a pre-irrigation soil moisture threshold of no less than 70% FC in the 0-50 cm layer of soil is mandatory. During the following phases of vegetative and reproductive growth, the soil moisture threshold in the 0–50 cm layer of soil must be kept at 80% FC to prevent unfavorable growth decline. In general, it is advisable to observe 70–80–70% FC in a 0–50 cm layer through the growing season of tomato in semi-arid climates to provide the crop with near-optimal growing conditions. Deviations from these optimal windows in any direction disrupt growth kinetics, artificially extend the critical period of the crop development, postpone fruit ripening and ultimately suppress overall crop productivity. Consequently, dynamic, stage-specific irrigation scheduling is highly recommended over continuous fixed-threshold regimes for semi-arid environments.

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