Physiological Simulation of *Arabidopsis thaliana* for Plant Digital Twin

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***Abstract*—The simulation of physiological plant growth is a foundation toward the development of a digital twin of plants in smart agriculture. The aim of this study is the development and validation of a physiological model capable of accurately simulating the biochemical dynamics of *Arabidopsis thaliana* under varying photoperiods. The model incorporates a wide range of internal and external parameters, including starch and sucrose dynamics, nitrogen and phosphorus levels, as well as biomass accumulation and assimilation costs. The simulation results were compared with experimental data from the literature and demonstrated a high degree of agreement in the dynamics of key processes during day/night cycles. These findings confirm the model's potential as a foundation for a plant digital twin, designed to integrate with real-time data.**

Keywords—digital twin, Arabidopsis thaliana, photoperiod, physiological model

I. Introduction

The development of digital twins of plants is gaining increasing application in the fields of smart agriculture and experimental botany, as it enables the prediction of plant behavior under various environmental conditions. Additionally, it can enhance farms sustainability and provide savings in water, fertilizer and pesticides usage [1]. The foundation of every digital twin lies in a faithfully represented physiological system capable of responding to dynamic inputs. In plant modeling, faithful representation of light, temperature, carbon dioxide concentration, nutrient concentrations, and more are essential for accurate representation of the complex interactions that drive plant growth and development under varying environmental conditions [2].

The focus is placed on the development and validation of a physiological model that simulates plant growth and development by monitoring parameters such as nitrogen, phosphorus, sucrose, starch, temperature, etc. The plan is to integrate this model into a broader digital twin system, where input values would be obtained from a combination of sensor devices (e.g., Arduino), satellite data, meteorological condition APIs, as well as predictions from weather models. In this way, adaptive and context-aware plant simulation in real time becomes possible.

First, the model description presents the core framework (photosynthesis, stomatal response, carbohydrate turnover, nutrient dynamics) together with the extensions introduced in this work. Then, the simulation setup is summarized, including photoperiod scenarios, environmental drivers, shared initial conditions, the ODE45 solver with hourly sampling, and the main assumptions and calibrations. Next, the validation part details the datasets and procedures used to compare simulations with literature measurements across several photoperiods and their results. Following this, the discussion interprets photoperiod sensitivity, explains deviations at short and long day lengths, and notes limitations with implications for digital twin applications. Finally, the concluding section summarizes the main findings and outlines next steps, including calibration of light-dependent photosynthesis and respiration, refinement of biomass allocation, separation of shoot and root nutrient pools with explicit free amino acid and nitrate pools, and integration of real-time data streams with a 3D growth visualization.

II. MODEL DESCRIPTION

The developed physiological model builds upon the model proposed by Tedone in his PhD thesis, which provides the baseline for simulating core processes of plant growth. Tedone's model focused on the balance between photosynthesis, carbohydrate storage, and nutrient assimilation, offering a robust starting point for describing the dynamics of primary metabolism [3].

Within the present work, two major extensions were introduced. The first concerns the representation of photosynthesis, which was reformulated through the integration of the Farquhar model. The Farquhar framework captures the biochemical limitations of carbon fixation, explicitly considering both the Rubisco-limited and electron transport-limited phases of photosynthesis. This extension enables the simulation to account for varying light intensities and CO_2 concentrations, thereby providing a more realistic depiction of possible variations under different photoperiod regimes [4], [5].

The second extension involved the incorporation of Jarvis-type functions, which link photosynthetic activity with environmental stress [6], [7]. These empirical formulations describe how stomatal conductance responds to external variables such as light, temperature, humidity, and soil moisture. By introducing this mechanism, the model reduces photosynthetic efficiency under suboptimal conditions, thereby establishing a direct connection between environmental and internal physiological processes.

Other physiological components, such as starch and sucrose dynamics, nutrient uptake and allocation, and biomass partitioning, are retained from Tedones original work with only minor adjustments for integration into the current simulation environment.

Overall, the model is structured as a modular framework in which environmental inputs (light, CO_2, nutrients, temperature) drive photosynthesis and stomatal behavior, which in turn regulate carbohydrate metabolism and nutrient assimilation. These processes collectively determine biomass production and growth dynamics. This modular organization not only facilitates validation against experimental data but also provides a flexible basis for future integration with real-time sensor inputs and digital twin applications.

III. Simulation Setup

This section specifies the common simulation configuration used throughout the study to ensure reproducibility and a fair comparison across photoperiods.

A. *Environmental drivers and scenarios*

Simulations were executed independently for each photoperiod with 4, 6, 8, and 12 hours of light per 24 hours over a 30-day growth period. The light regime used a square wave schedule with a fixed lights on and lights off window each day. Only day length differed between scenarios. Water stress was not imposed. Jarvis moisture and vapor pressure deficit response factors were kept at non limiting levels. All runs shared the same initial conditions for carbohydrate pools, nutrient pools, and total biomass. The parameterization was fixed across photoperiods so that behavioral differences arise from light duration rather than from parameter changes.

B. *Numerical integration and outputs*

The differential equations were solved using an adaptive ODE45 integrator with automatic step size control. Internal solver steps were variable, while model states were sampled at 1-hour intervals for plotting and quantitative comparison with reference time courses from the literature. Units were harmonized across variables and studies. For example, µmol per gram fresh weight for metabolites and grams fresh weight for biomass. When literature values were reported on a dry weight basis, a literature based fresh weight to dry weight conversion factor for *Arabidopsis thaliana* at a comparable developmental stage was applied to align units for comparison [8]. The same factor was used consistently across datasets. Beyond resampling, unit alignment, and the fresh weight to dry weight conversion, no additional scaling of simulation outputs was applied. Where sources reported multiple biological replicates, the published mean trajectory was used as the reference.

C. *State variables*

The state vector comprised sucrose, starch, total nitrogen, total phosphorus, and cumulative biomass. Photosynthetic carbon gain supplied daytime sucrose. Starch accumulated during the light period and was mobilized overnight. Sucrose supported growth, maintenance, and respiration. Nitrogen and phosphorus reflected uptake from the environment and allocation to growth costs, which modulated biomass production. Biomass increased according to net assimilation after accounting for maintenance and assimilation costs. Using a common parameter set for all photoperiods ensures that observed differences in metabolite dynamics and relative growth rates can be attributed to light duration.

IV. Validation of the Simulation Model

The validation of the physiological plant growth model is conducted using experimentally obtained data from relevant scientific literature, with *Arabidopsis thaliana* employed as the reference species. The primary objective of this validation is to assess the accuracy of the simulation in comparison to actual measurements of biochemical and morphological parameters over a 30-day plant development period. The validation was conducted in multiple photoperiods. Specifically, 4, 6, 8 and 12 hours of light exposure per day with intention to evaluate the influence of photoperiod on physiological processes.

Particular emphasis is placed on the dynamic behavior of key parameters, such as starch and soluble sugars, as well as macronutrients including nitrogen and phosphorus. Additionally, the relative growth rate (RGR) is monitored as an indicator of the overall efficiency of biomass accumulation under different environmental conditions.

For evaluation purposes, multiple independent sources from the scientific literature are utilized [8], [9], [10], containing detailed measurements of the mentioned parameters, including studies that quantify metabolite dynamics over the day/night cycle as a function of photoperiod duration. This approach enables cross-comparison with datasets, providing a more comprehensive and robust validation of the model.

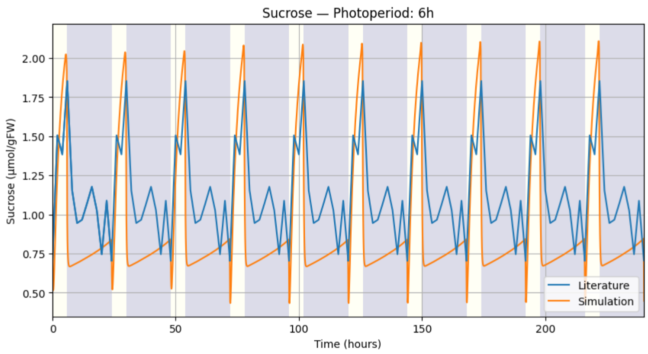

Fig. 1 Changes in sucrose concentration under a 6-hour photoperiod. Experimental data (blue) and simulation results (orange)

Figure 1 shows the changes in sucrose concentration during a 24-hour cycle under a 6-hour photoperiod. Experimental (literature-based) data [8] are represented in blue, while the results of the developed simulation model are shown in orange. The simulation captures the characteristic daily oscillations of sucrose, with peaks during the light phase and a decrease during the night. Although the general rhythm is well reproduced, a deviation in amplitude is observed.

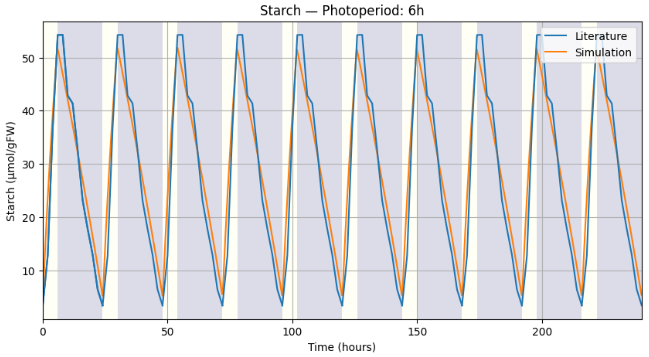

Fig. 2 Changes in starch concentration under a 6-hour photoperiod. Experimental data (blue) and simulation results (orange).

Figure 2 presents the changes in starch concentration under the same 6-hour photoperiod. Starch accumulation during the light period and its degradation during the night are clearly visible. The simulation successfully reproduces this day/night pattern and closely follows the literature data, confirming the reliability of the model in capturing starch dynamics.

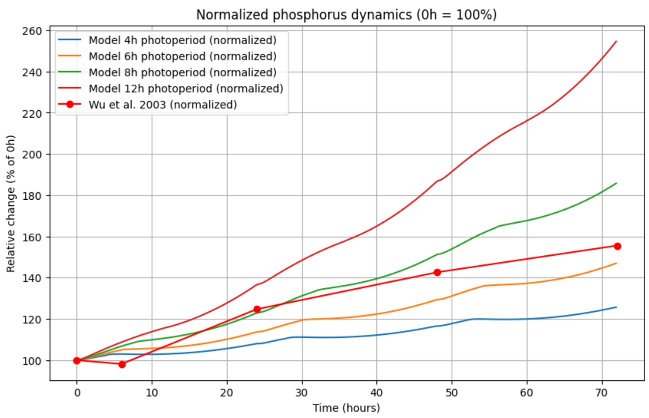

Fig. 3 Normalized phosphorus dynamics under different photoperiods (4h, 6h, 8h, 12h) expressed relative to initial levels (0h = 100%). Model results are compared with experimental data from [9]

Figure 3 shows the 72-h time course of total plant phosphorus (P), after the 30 days of growth, from the literature [9] alongside simulations under 4 h, 6 h, 8 h, and 12 h photoperiods. Model outputs (µmol P g^{-1} FW) were converted to mg P $plant^{-1}$, and normalized to the 0 h value to emphasize temporal behavior while minimizing scale differences due to tissue partitioning and units.

Experimental source does not report the exact photoperiod, thus similarity is evaluated at the level of curve shape (relative accumulation trajectory) rather than absolute magnitude. Under intermediate photoperiods (6–8h) the simulated trajectory shows clear similarity with the literature trend, while 4 h shows a flatter profile and 12 h a steeper one. Thus, despite the unknown photoperiod, the model reproduces the characteristic pattern of phosphorus build-up over three days, with the 6–8h scenarios providing the most representative match in shape.

These results demonstrate that the physiological model can reproduce the daily dynamics of sucrose, phosphorus and starch with good accuracy, which is an important step toward developing a reliable digital twin of the plant. Further refinements may include parameter adjustments for photosynthesis and the inclusion of additional metabolites such as glucose, fructose, and total soluble sugars.

TABLE I. COMPARISON OF MODEL-PREDICTED AND LITERATURE-BASED RELATIVE GROWTH RATE (RGR) VALUES ACROSS MULTIPLE PHOTOPERIOD CONDITIONS. THE CALCULATED PERCENTAGE ERROR INDICATES THE DEVIATION OF SIMULATION RESULTS FROM EXPERIMENTAL REFERENCE DATA.

Photoperiod (h)	**RGR model**	**RGR literature**	**Error (%)**
4	0.05972	0.068	12.17%
6	0.10287	0.1135	9.36%
8	0.18034	0.1708	5.58%
12	0.28773	0.26	10.66%

Table 1 summarizes the comparison between the simulated RGR and literature RGR at 4, 6, 8, and 12h of light. Quantitatively, the deviations are 12.2% (4 h), 9.4% (6h), 5.6% (8h), and 10.7% (12h), yielding a mean absolute percent error of ~9.4%. The smallest difference occurs at 8 h, indicating the best match.

The sign of the deviations is consistent across the range: the model underestimates RGR at shorter days (4h, 6h) and overestimates at longer days (8h, 12h). This pattern suggests that the simulated growth response scales weakly at short photoperiods and stronger at long photoperiods. In practice, this points to modest calibration opportunities in the light-dependent components, while overall similarity remains good and in line with the phosphorus analysis, where 6–8 h also provided the most representative match.

V. DISCUSSION

Across 4 to 12 hours of light the model reproduces the daily behavior of sucrose and starch and the multi day build up of phosphorus, consistent with reported photoperiod dependent carbon allocation in Arabidopsis [8]. The smallest RGR deviation occurs at 8 hours. Under short days the model tends to underestimate RGR and slightly underpredict sucrose amplitude. This points to light dependent assimilation or stronger maintenance costs during short photoperiods, in line with established photosynthesis and respiration scaling used in leaf level modeling [4], [5].

Phosphorus trajectories compared with the literature show the correct qualitative pattern of accumulation over three days [9]. The best shape similarity is again found for intermediate photoperiods. The experimental source does not report the exact photoperiod so the evaluation is necessarily based on curve shape rather than absolute magnitude. The same parameter set was used for all photoperiods which supports the interpretation that day length alone can explain most of the observed variation. Residual differences likely reflect nutrient uptake saturation and allocation assumptions that were kept simple for this study [3].

Environmental drivers were idealized and water stress was not imposed which simplifies the interpretation but exclude important variability. Circadian control of starch turnover was represented implicitly through simple kinetics. These choices keep the model compact while leaving clear targets for calibration and structural refinement. For digital twin use the current accuracy is already useful for analysis and for near real time monitoring when coupled to sensor streams and weather predictions [1], [2].

VI. Conclusion

This work presented a physiological model of Arabidopsis thaliana that integrates photosynthesis (Farquhar), stomatal response (Jarvis-type functions), carbohydrate turnover, and nutrient dynamics to simulate growth under varying photoperiods. Validation against literature data shows that the model reproduces the diurnal behavior of sucrose and starch under a 6h photoperiod and captures the multiday build-up of phosphorus when curves are compared in normalized form. Because the experimental source for phosphorus does not report the exact photoperiod, agreement was assessed at the level of curve shape, where the 6–8 h simulations provide the closest trajectories, while 4 h is flatter and 12 h steeper. Relative growth rate (RGR) increases with day length in both the model and literature; the mean absolute percent difference across photoperiods is ~9.4%, with the smallest deviation at 8 h. Together, these results indicate that the model reproduces key physiological trends with useful accuracy and provides a credible basis for a plant digital twin.

Future efforts will focus on calibration of light-dependent photosynthesis, respiration parameters, and biomass allocation to reduce the observed errors at short and long photoperiods. Structural extensions will be added to separate shoot–root nutrient pools and to introduce dedicated “free amino acid” and nitrate pools, enabling direct comparison to metabolite datasets. Finally, data assimilation from real-time sources (weather APIs, satellite/NDVI products, and low-cost IoT sensors) and linkage to a 3D growth visualization will be implemented.

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