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学位論文全文に代わる要約
Extended Summary in Lieu of Dissertation

氏名：
Name Yayu Romdhonah

学位論文題目：
Title of Dissertation
Studies on the high time-resolution net photosynthetic rates of cherry tomato plants: Empirical models and seasonal changes
(高時間分解光合成速度計測データを用いたミニトマト個体群の光合成モデリング)

学位論文要約：
Dissertation Summary

Chapter 1. General Introduction

Net photosynthetic rate (P_n), defined as net CO_2 uptake, is essential in diagnosing plant physiological activities as a response to the environmental factors. It is an indication of actual plant growth, as well as a guide tool for greenhouse control based on the speaking plant approach (SPA). Recently, P_n measurement techniques have advanced from single-leaf to whole-plant level under greenhouse conditions. Moreover, the current technology of real-time remote sensing devices enables high time resolution, non-contact, non-intrusive measurement systems like the novel photosynthesis chamber of Shimomoto et al. (2020) does.

Cherry tomato is a particularly interesting case for the photosynthesis study by using the novel chamber system due to several reasons: (1) it is of high economic value, especially in the summer season, (2) not much is known about the whole-plant photosynthetic rate of cherry tomato, (3) its complicated canopy architecture with different light distribution within the vertical can be a model plant to represent other plants with the same canopy characteristics. The present study used and analyzed the high time-resolution P_n of cherry tomato (*S. licopersicum* var. *cerasiforme*) cv. Scarlet under greenhouse conditions measured by the chamber. The objectives were to develop a P_n estimation model for cherry tomato plants and to gain an understanding of how plants interact with their aerial environment.

Chapter 2. The High Time-resolution Net Photosynthetic Rates of Cherry Tomato Plants

Measurements of the whole-plant net photosynthetic rates of mature cherry tomato plants were conducted in spring, summer, and winter in a commercial greenhouse in Mie Prefecture, Japan, by using the aforementioned chamber (Fig. 1). The greenhouse environment was optimized by a commercial microcomputer. In spring and summer, the opening and closing of greenhouse windows depended on the greenhouse condition to maintain the right temperature and the right humidity. In summer, shading was applied on sunny days at noon around 11:00 to 14:00. In winter, heating was used to maintain the base air temperature of 17°C, and no supplemental lighting was applied. In addition, the rate of CO_2 supply was 530 ppm to maintain the set point of 500 ppm/day in all seasons. There was no fixed time for irrigation. It depended on the needs of the plants based on the water content of the slab measured by a sensing device.

The continuous measurements in high time resolution with 5-min interval established typical diurnal changes in each season. Distinct diurnal changes occurred due to different lengths of daytime. Also, the variation of the changes existed due to climatic factors and different greenhouse control applied in the season. Net photosynthetic rate generally increased significantly at the start of the day (after sunrise), maintained at a high level at noon, and then decreased during the afternoon hours as the sun went down. Plotting the 30-min moving average P_n with the corresponding *I*, *T*, *C*, *RH*, and *VPD* was useful to emphasize the diurnal pattern in CO_2 exchanges. Under the prevailing greenhouse condition, photosynthesis was driven by *I*, enhanced by *C* and limited by *VPD*.

A linear model to estimate canopy P_n (μmol chamber^{-1} s^{-1}) by using the original 5-min interval of high time-resolution P_n resulted in a moderate accuracy (R^2 = 0.63; RMSE = 3.799 μmol chamber^{-1} s^{-1}). The P_n was expressed as a linear function of instantaneous PAR above the canopy (*I*, W m^{-2}), air temperature (*T*, °C), vapor pressure deficit (*VPD*, mmol mol^{-1}), and CO_2 concentration (*C*, μmol mol^{-1}). The study implied for further data processing to improve model accuracy.

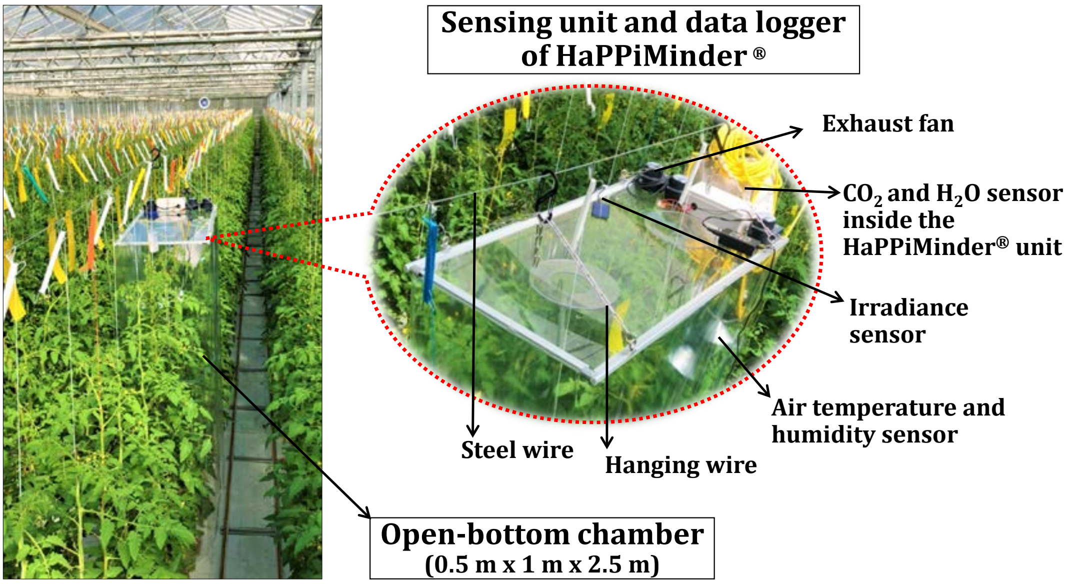

Fig. 1 The novel photosynthesis monitoring chamber system of Shimomoto et al. (2020) for net photosynthetic rate measurements under a commercial greenhouse.

Chapter 3. Averaging Techniques in Processing the High Time-Resolution Photosynthesis Data of Cherry Tomato Plants for Model Development

The next study of the model development encompassed averaging techniques in processing the original data by applying a moving average (*MA*) and simple average (*SA*) with several time frames (30-min, 1-h, 2-h). A multiple regression analysis in SPSS ver 25 was used to establish the models. Data on spring measurements were used for this study. Model accuracy generally increased with longer time frames; however, it can be varied depending on the datasets and the variables used in the models. The 2-h simple average datasets gave the best accuracy for both 5-variable model (*I*, *T*, *RH*, *VPD*, *C*) and 3-variable model (*I*, *VPD*, *C*) with R^2 of 0.81 and 0.67, respectively. This study indicated that datasets of a 2-h time frame with a simple average were promising to make a practical general linear regression model.

Chapter 4. Practical Photosynthesis Model for Cherry Tomato using the High Time-resolution Photosynthesis Data

Further study was conducted by using a 10-day dataset processed with a 2-hour simple average to estimate the next five-day P_n. In this study, four linear models by four variables ((*I*, *T*, *RH*, *C*) were explored namely the general linear model (Model A), the linear interaction model (Model B), the linear-quadratic model (Model C), and the linear interaction-quadratic model (Model D). The regression learner application in MATLAB® R2019a was used to establish the models by using processed data of summer measurement. The stepwise method was used to select the variables included in each model. As a result, models A, B, C, and D correspond to Equation 1, 2, 3, and 4, respectively. The P_n by Eq. 4 (Model D), which expressed as a linear function that incorporated the quadratic and interaction components of *I*, *T*, and *C*, resulted best. The model estimated P_n with high accuracy (R^2 = 0.94, RMSE = 1.727 μmol chamber^{-1} s^{-1}) and performed well on both sunny and rainy conditions, but with lower time resolution. The study implied that further data processing has succeeded in increasing model accuracy. The model is more suitable for long-term analysis meaning that under the prevailing optimized condition in summer, the dominant factors contributing to P_n were *I*, *T*, and *C*.

$$P_n = \alpha_0 + \alpha_1 I + \alpha_2 T + \alpha_3 C + \alpha_4 VPD \quad (1)$$

$$P_n = \beta_0 + \beta_1 I + \beta_2 T + \beta_3 C + \beta_4 VPD + \beta_5 I \times T + \beta_6 I \times VPD + \beta_7 T \times VPD \quad (2)$$

$$P_n = \gamma_0 + \gamma_1 I + \gamma_2 T + \gamma_3 C + \gamma_4 I^2 \quad (3)$$

$$P_n = \delta_0 + \delta_1 I + \delta_2 T + \delta_3 C + \delta_4 I \times T + \delta_6 I^2 + \delta_7 T^2 \quad (4)$$

where P_n is in units of μmol chamber^{-1} s^{-1}, *I* is in units of W m^{-2}, *T* is in units of °C, *C* is in μmol mol^{-1}, *VPD* is in μmol mol^{-1}, and α, β, γ, and δ are regression coefficients.

Chapter 5. Whole-plant Net Photosynthetic Rate Model for Cherry Tomato under Commercial Greenhouse using the High Time-resolution Photosynthesis Data

For a higher time-resolution estimation, further study was conducted by using a 10-day dataset processed with a 5-point moving average of the original data to estimate the next five-day P_n. In this study, Model A, B, C, and D, as in Chapter 4, were trained with the processed data by using the regression learner application in MATLAB® R2019a. The stepwise method selected the significant variables for each model. As a result, models A, B, C, and D correspond to Equation 5, 6, 7, and 8. The whole-plant P_n (μmol plant^{-1} s^{-1}), expressed as a linear function that incorporated the quadratic and interaction components of *I*, *T*, *VPD*, and *C* as in Model D (Eq. 8), resulted best. Estimations of P_n were agreed well (R^2 = 0.89, RMSE = 1.471 μmol plant^{-1} s^{-1}). Model validation with a sunny and rainy day showed that the model could predict well despite the dynamic changing of P_n as a response to the dynamic changing of environmental factors. Figs. 2 and 3 show the time course of measured and estimated whole-plant photosynthetic rate for test dataset on a sunny day on 24th June (*n* = 183) and a rainy day on 23rd June 2018 (*n* = 181), respectively.

$$P_n = \alpha_0 + \alpha_1 I + \alpha_2 T + \alpha_3 C + \alpha_4 VPD \quad (5)$$

$$P_n = \beta_0 + \beta_1 I + \beta_2 T + \beta_3 C + \beta_4 VPD + \beta_5 I \times T + \beta_6 I \times C + \beta_7 I \times VPD + \beta_8 T \times C + \beta_9 T \times VPD + \beta_{10} C \times VPD \quad (6)$$

$$P_n = \gamma_0 + \gamma_1 I + \gamma_2 T + \gamma_3 C + \gamma_4 VPD + \gamma_5 I^2 + \gamma_6 T^2 + \gamma_7 C^2 + \gamma_8 VPD^2 \quad (7)$$

$$P_n = \delta_0 + \delta_1 I + \delta_2 T + \delta_3 C + \delta_4 VPD + \delta_5 I \times T + \delta_6 I \times C + \delta_7 I \times VPD + \delta_8 T \times C + \delta_9 T \times VPD + \delta_{10} C \times VPD + \delta_{11} I^2 + \delta_{12} T^2 + \delta_{13} C^2 + \delta_{14} VPD^2 \quad (8)$$

where P_n is in units of μmol plant^{-1} s^{-1}, I is in units of W m^{-2}, C unit is μmol mol^{-1}, VPD is in kPa, and α, β, γ, and δ are regression coefficients.

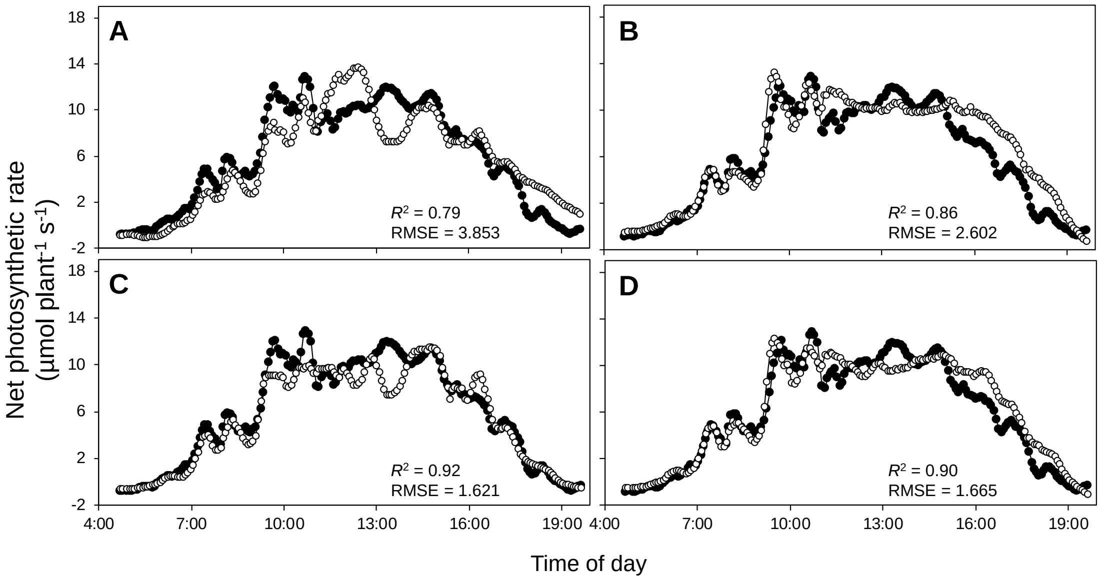

Fig. 2 Measured (black dot) and estimated (white dot) whole-plant photosynthetic rate for test dataset (n = 183) on a sunny day on 24th June 2018 of Equation 5 (A), Equation 6 (B), Equation 7 (C), and Equation 8 (D).

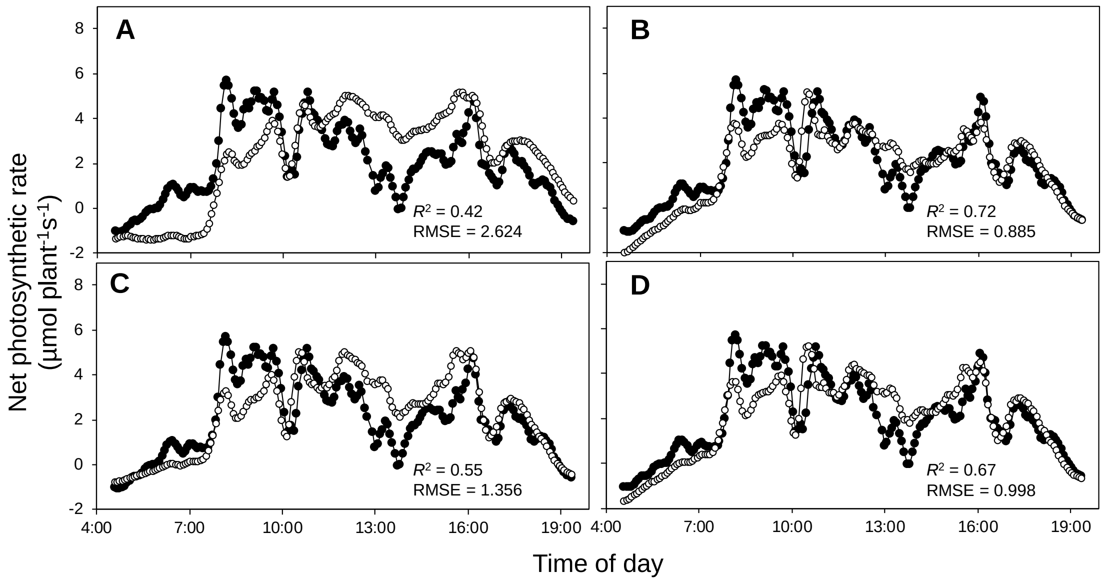

Fig. 3 Measured (black dot) and estimated (white dot) whole-plant photosynthetic rate for test

dataset (n = 181) on a cloudy day in 23rd June 2018 of Equation 5 (A), Equation 6 (B), Equation 7 (C), and Equation 8 (D).

Chapter 6. Summary

The results of the present study suggest that whole-plant P_n of cherry tomato plants can be empirically estimated from aerial environmental factors without including the leaf area into the function by using the high time-resolution photosynthesis data. The study implied that by applying feature engineering, a linear model could fit the high time-resolution photosynthesis data and was able to estimate whole-plant P_n in reasonable accuracy. Further study to implement the model in process computer control at a greenhouse is needed. Once the system has been settled, the controlling of greenhouse environmental factors based on the SPA becomes feasible.

References

Shimomoto, K., Takayama K., Takahashi, N., Nishina, N., Inaba, K., Isoyama, Y., and Oh, S., 2020. Real-time monitoring of photosynthesis and transpiration of a fully-grown tomato plant in greenhouse. Environ Control Biol. **58**: (in press).

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