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SIMULATION AND CALIBRATION OF EXTENDED HORTSYST MODEL IN PREDICTING MACRONUTRIENTS IN TOMATO (*Solanum lycopersicum* L.)

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SIMULATION AND CALIBRATION OF EXTENDED HORTSYST MODEL IN PREDICTING MACRONUTRIENTS IN TOMATO (*Solanum lycopersicum* L.)

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RESUMEN GENERAL

SIMULACIÓN Y CALIBRACIÓN DEL MODELO HORTSYST EXTENDIDO EN PREDICCIÓN DE MACRONUTRIENTES EN TOMATE (*Solanum lycopersicum* L.)

El potencial de producción de altos rendimientos de los cultivos está latente en México, pero debe de hacerse con moderación para no seguir aumentando la contaminación y ahorrar costos de producción con el uso óptimo de fertilizantes. El modelo dinámico HortSyst que predice la producción de materia seca (PMS) se calibró y evaluó para el tomate cultivado desde el trasplante hasta el comienzo de la fase reproductiva en un invernadero de plástico ubicado en la parte central de México, utilizando datos del verano-otoño de 2018, parámetros actualizados del cultivo y un paso de tiempo de 5 min. El rendimiento del modelo HortSyst sin calibración, con la predicción de PMS tuvo una eficiencia (EF) de 0.91 y una eficiencia de uso de radiación (EUR) de 4.86 g MJ^{-1} m^{-2} RFA, fallando en la simulación de la magnitud de la fluctuación entre las mediciones, en comparación con el calibrado que fue incapaz de simular el patrón de fluctuación a través de mediciones con una EF 0.99 y RUE 5.89 g MJ^{-1} m^{-2} RFA. Para modelar las concentraciones de macronutrientes (N, P, K, Ca y Mg) se utilizaron modelos gaussianos y una curva polinómica, mediante la de tasa de desarrollo relativa acumulada como entrada (TDRa), lo que resultó en un coeficiente de determinación (R^2) de 0.99 para los modelos N, P, Ca y Mg y R^2 de 0.86 para el modelo K. Para determinar la absorción de macronutrientes, la concentración de los nutrientes se multiplicó por el peso producido, obteniendo un EF mayor a 0.98 en las simulaciones para todos los macronutrientes.

Palabras claves: tomate, macronutrientes, modelos de simulacion.

GENERAL ABSTRACT

SIMULATION AND CALIBRATION OF EXTENDED HORTSYST MODEL IN PREDICTING MACRONUTRIENTS IN TOMATO (*Solanum lycopersicum* L.)

The production potential of high crop yields is latent in Mexico, but it must be done in moderation so as not to continue increasing pollution and save production costs with optimal fertilizer use. The HortSyst dynamic model which predicts dry matter production (*DMP*) was calibrated and evaluated using data from the summer to fall 2018, actualized crop parameters and a time step of 5 min, for tomato grown from transplant until the beginning of the reproductive phase in a plastic greenhouse located at the central part of Mexico. The HortSyst model performance without calibration as predicting *DMP* had an efficiency (*EF*) of 0.91 and a radiation use efficiency (*RUE*) of 4.86 g MJ^{-1} m^{-2} *PAR*, failing to simulate the magnitude of the fluctuation between measurements, compared with the calibrated that failing to simulate the fluctuation pattern through measurements with *EF* 0.99 and *RUE* 5.89 g MJ^{-1} m^{-2} *PAR*. In order to modeling macronutrients (N, P, K, Ca and Mg) concentrations, Gaussian curves and a polynomial curve using as an input cumulative relative development rate (*RDRc*) were used, which resulted in a coefficient of determination (R^2) of 0.99 for N, P, Ca and Mg models and R^2 of 0.86 for K model. To determine macronutrients uptake, the concentration of the nutrients was multiplied by the weight produced, resulting in an EF greater than 0.98 in the simulations for all macronutrients.

Keywords: tomato, macronutrients, simulation models.

Thesis in Master in Agricultural Engineering and Integral Water Use, Universidad Autónoma Chapingo

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GENERAL INTRODUCTION

The simulation of nutrients dynamic behavior in crops has emerged from the need to optimize the resources, such as fertilizers, used in crop production. Nowadays, in a globalized world, people are more aware that natural resources are not limited and high competition pushes all companies to be more efficient in their productive chain. The first models of plant nutrition were born to explain the physiological and physical processes so that the nutrients moved from the soil to the plant. Those models were mainly theoretical and complex. With the arrival of modern and precise computer systems and electronic sensors, and with the help of statistics, the models evolved to be simpler without losing precision, in combination with more sophisticated fertilization systems, they are part now of the precision agriculture. Thus, current plant nutrition models are closer to practical applications.

3.1. JUSTIFICATION

The production of national tomato (*Solanum lycopersicum* L.) is mostly carried out in soil and with the use of large amounts of fertilizers, so to avoid a negative environmental impact, it is necessary to make optimal use of these, because demand continues to increase. Utilizing the extended HortSyst model as a decision support system to fertilizer application.

3.2. HYPOTHESIS

1. Updating the parameters, based on recent research and reducing simulation time, would increase the accuracy of the HortSyst model.

2. The nutritional concentration in the plant is based on the state of development of the plant.

3.3. OBJECTIVE

The objective of the current work is to extend the HortSyst model, updating parameters, modifying the simulation time step and adding macronutrients uptake models to increase the accuracy of the model and macronutrients simulated.

LITERATURE REVIEW

The progress of agricultural knowledge has allowed humans to dominate life itself, being able to select where, when and how it will develop even under the most adverse conditions, whose only limitation is water availability.

Tomato crop (*Solanum lycopersicum* L.) is probably the most important vegetable crop on a worldwide basis (Dixon & Aldous, 2014). Mexico is the leading exporter of tomato worldwide covering 25.11% of the international market, with a participation of 3.46% of the national agricultural PIB (SAGARPA, 2017). The world agricultural competition focuses on maintaining a constant production throughout the year without neglecting the ecological, social and economic issues.

Nowadays, with the fusion of agronomic, mathematics, electronic and computer science (agricultural and biosystems engineering), it has allowed the more precise development of mathematical models that explain physiological processes that explain the growth of the crop. Allowing us to predict the behavior of the plant under hypothetical growth environment, saving supplies, workforce and with the least environmental impact. A mathematical model is an equation or a set of equations which demeanor is a system (Thornley & France, 2007), and can be classified into different categories: representation of processes, static versus dynamic, continuous versus discrete and deterministic versus stochastic. Representation of processes can be mechanistic, explicit representation, or empirical, which rely on statistical equations. Static versus dynamic where a static model does not account for the element of time, while a dynamic model does. Continuous versus discrete is the way that the time is considered. Deterministic versus stochastic where the randomness is presented in stochastic models. (Soltani & Sinclair, 2012). The most usual models are mechanistic and empirical. The empirical models are direct descriptions of observed data, where any proposed mathematical relationship is not restricted by any physical, thermodynamic laws or biological information (Rodriguez et al., 2015). The

Mechanistic models understand or explain the phenomenon. To make that, the model must to establish at least two levels of description (Thornley & France, 2007).

“Plants represent some of the most difficult biological systems to model. There are major problems with choosing the appropriate spatial, temporal, and biological scales” (Haefner, 2005). To study growth and development of the crops, it is necessary to understand the biotics and abiotics elements that affect them. The fundamental physiological processes in plants are: photosynthesis, respiration, nutrients and water (uptake and transport). Most of the explanatory models are based on photosynthesis. (Rodriguez et al., 2015).

General growth function connecting dry weight (W) to time (t) is:

$$W = f(t) \quad [1]$$

where f denotes some functional relationship (Thornley & France, 2007), like the basic physiological processes in plants.

TOMGRO (Jones et al, 1991) is a mechanistic model to predict development and growth (yield) of different organs for the tomato crop, to respond to dynamically changes of temperature, solar radiation and CO2 concentration. It has seven state variable vectors consisting of physiological age classes of plant components: numbers of leaves, numbers of main stem segments, numbers of fruits, dry weights of leaves plus petioles, dry weights of main stem segments, dry weights of fruits, and areas of leaves. The model also has nine functional relationships that must be determined empirically, and 21 coefficients that have to be quantified. Development and abortion function, of TOMGRO model, were validated in 1991 by Bertin & Gary (1993), concluding on some points that cannot be explained entirely by the model as steam strength that was supposed to be a constant fraction of potential leaf expansion, but this leads to an overestimated dry matter at the end of the period and among different tomato cultivars dry matters can vary ratios between supply and demand. In the most complete version, TOMGRO v3.0

can have 574 state variables and simulate with great detail the development of fruits (Rodriguez et al., 2015). In 1999 was published a simplified version of TOMGRO (Jones et al., 1999) with the objective of development a dynamic tomato growth model with a minimum number of state variables reducing the state variables to five (Number of nodes on mainstem, leaf area index, aboveground dry weight, total fruit dry weight and mature fruit dry weight). It was evaluated by Bacci et al. (2012) and confirmed that the simplified version of TOMGRO can be easily adapted to different growing conditions but they found some difficulties in the estimation of node and leaf area index (LAI).

TOMSIM (Heuvelink, 1995) is a mechanistic model with a modular structure, which simulate tomato crop growth and development utilizing 19 parameters. Concluding after 14 experiments that only under extreme crop condition (low light, large crop dry weight) is growth rate under estimated. TOMSIM (Heuvelink, 1996) is an improvement version, simulating the dry matter portioning by the sink organs based in leaf photosynthetic rate. It is necessary to have data for the 24 h of temperature, light intensity and carbon dioxide concentration (Rodriguez et al., 2015). TOMSIM (Heuvelink, 1996) was evaluated by (Ramirez et al., 2004), resulting in 10% of error in the total dry weight prediction and was found that the model is sensitive to the effect of light use efficiency in absence of oxygen.

Improving the efficiency of nutrients through a better prognosis of when and where fertilizers are required is aimed at improving crop yields without sacrificing the ecological part. In some parts of the world there is an over fertilization in crops like in China, while in others an under fertilization like in Kenya (Barker & Pilbeam, 2015). The first nutrient uptake models assumed that the roots are uniformly distributed in homogeneous and isotropic soil having no temporal and spatial gradients (Rengel, 1993). Those models were more focused and understood the movements of the elements through the plant-soil system, than just predicting the amount of nutrient absorbed by the plant, using the root geometry and describing kinetics of nutrient uptake, so that a review (Rengel, 1993) concluded the applicability of nutrient uptake models to the agricultural practice is still rather blurred.

Nye-Tinker-Barber model (1970) for nutrient uptake by a single cylindrical root where the nutrients are transported along of root by convection due to water uptake by the plant, and by diffusion of ions in the soil pores. The relation between the net influx of nutrients and the concentration was described by Michaelis-Menten type uptake law (Roose, 2000).

Individual nutrient uptake model (Makin & Fynn, 1996), is based on the assumption that actual plant nutrient uptake (U_n, mg m^{-2} h^{-1}) is ultimately driven by nutrient demand (D_n).

$$U_n = D_n \pm X_n \qquad [2]$$

where X_n, is positive for luxury consumption of nutrients, and negative when plants draw on stored nutrients to help meet a current demand.

Model (Eq. 2) uses the rate of the net photosynthesis, the rate of nutrient uptake, a Michaelis-Menten constant and the intercepted photosynthetic photon flux density.

VegSyst (Gallardo et al., 2011) model simulates crop biomass production, crop N uptake and crop evapotranspiration with daily data of maximum and minimum temperature, maximum and minimum relative humidity, integral solar radiation and latitude. The model assumes that crops have no water or nutrient limitations. VegSyst was development to simulate muskmelons (Gallardo et al., 2011) and peppers (Gimenez et al., 2012) and until 2014 was calibrated and evaluated with tomato (Gallardo et al., 2014), driven by thermal time to calculate daily biomass production, N uptake and evapotranspiration, suggesting in this research the potential for adapting the model to other crops. VegSyst simulates dry matter production (Eq. 3) based on the fraction of intercepted *PAR* and *RUE* and simulate N uptake (Eq. 5) using dry matter to calculate nitrogen concentration (Eq. 4) as an exponential function.

$$DMP_i = PAR_i * RUE \quad [3]$$

$$\%N_i = a * DMP_i^b \quad [4]$$

$$N_{up} = DMP_i * \%N_i \quad [5]$$

where *PAR* s the fraction of intercepted photosynthetically active radiation, *RUE* is the radiation use efficiency (g MJ^{-1}); *a* and *b* are calibrated factors.

VegSyst V2 (Gallardo et al., 2016) is a revised simpler model, some of the changes included Almeria radiation method to estimate daily evapotranspiration, that only require values of greenhouse transmissivity and daily temperature or daily solar radiation (Fernández et al., 2010), the growth model was reduced to one phase, the maximum fraction of intercepted PAR radiation is maintained to the end of crop, this model was calibrated and validated for several varieties of cucumber, zucchini, melon, pepper, watermelon and eggplant.

HortSyst (Martínez-Ruiz et al., 2019) is discrete time model for describing the dynamics of photo-thermal time (PTI), total dry matter production (*DMP*), N uptake (N_{up}), leaf area index (*LAI*) and evapotranspiration (*ETc*). This model is based on VegSyst whence they share several similarities, some of the changes proposed in HortSyst model are:

$$TT = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \leq T_a < T_{ob}) \\ 1 & (T_{ob} \leq T_a \leq T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \leq T_{max}) \\ 0 & (T_a > T_{max}) \end{cases} \quad [6]$$

where TT is the normalized thermal time, T_a is air temperature, T_{min} is the minimum temperature, T_{max} is the maximum temperature, T_{ob} is the lower optimal temperature and T_{ou} is the upper optimal temperature.

$$\Delta PTI_i = {(\sum_{h=1}^{24} TT(h,i))}/{24} * PAR_i * f_{i-PAR} \quad [7]$$

Where f_{i-PAR} is the fraction intercepted of photosynthetically active radiation.

$$LAI_i = \frac{c_1 * PTI_i}{c_2 + PTI_i} d \quad [8]$$

Where c_1 and c_2 are parameters of the Michaelis-Menten equation and d is crop density.

4.1. CONCLUSION

Growth and development dynamic models for tomato crop have evolved from complex and theoretical models to simpler models with practical applications. Where the sections of the previous models from others authors, that better and more easily explained the processes were used, using statistics to avoid losing pressure on the way.

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SIMULATION AND CALIBRATION OF EXTENDED HORTSYST MODEL IN PREDICTING MACRONUTRIENTS IN TOMATO (*Solanum lycopersicum* L.)

5.1. ABSTRACT

The potential of greenhouse crops is latent in Mexico, but this has to be done with restraint so as not to continue increasing pollution and save production costs with the use of fertilizers. It is during the vegetative phase that the inflorescence meristems begin their transformation, resulting in future bunches and tomato fruits. The HortSyst dynamic model which predicts dry matter production (*DMP*) was calibrated and evaluated using data from the summer to fall 2018, actualized crop parameters and a time step of 5 min, for tomato grown from transplant until the beginning of the reproductive phase in a plastic greenhouse located at the central part of Mexico. The HortSyst model performance without calibration as predicting *DMP* had an efficiency (*EF*) of 0.91 and a radiation use efficiency (*RUE*) of 4.86 g MJ^{-1} m^{-2} *PAR*, failing to simulate the magnitude of the fluctuation between measurements, compared with the calibrated that failing to simulate the fluctuation pattern through measurements with *EF* 0.99 and *RUE* 5.89 g MJ^{-1} m^{-2} *PAR*. In order to modeling macronutrients (N, P, K, Ca and Mg) concentrations, Gaussian curves and a polynomial curve using as an input cumulative relative development rate (*RDRc*) were used,which resulted in a coefficient of determination (R^2) of 0.99 for N, P, Ca and Mg models and R^2 of 0.86 for K model. To determine macronutrients uptake, the concentration of the nutrients was multiplied by the weight produced, resulting in an EF greater than 0.98 in the simulations for all macronutrients.

Keywords: tomato, macronutrients, simulation models.

5.2. INTRODUCTION

Tomato crop production covers almost a quarter of Mexican national vegetables production given that, in 2018 was 3.35 million of tons and its annual growth rate is estimated at 5.58% until 2030 (SAGARPA, 2017). Tomatoes are mostly cultivated in soil where a 59.6% is covered with shade houses or greenhouses (FIRA, 2016). Latin America & Caribbean have a negative balance between supply and total demand fertilizer in terms of N, P_2O_5 and K_2O (FAO, 2016), applying less fertilizers than those demanded by plant leaving space for Mexican production to grow in terms of profitability instead of area produced. Figures from

2004-2018 showed a growth in yield (230%) and a decrease in the area produced (-39.98%) in Mexico (SIAP, 2019). The cost of using fertilizers to boost tomato cultivation in Mexico ascends to 1.3% (Navarro, 2011) or 4.3% (Morales & Gonzales, 2017) of total investment for a production unit so an optimal use of these, it's of special interest so much for to reduce production costs and to avoid waste, soil contamination and underground aquifers, a way to sustainable agriculture. "Unofficially, the National Water Commission recognizes that agricultural discharges, deforestation and poor waste management cause 70% of the contamination of water bodies in our country" (Aguilar & Perez, 2008).

Crop growth refers to the increment of biomass or plants dimensions that can be measurements (Goudriaan & van Laar, 1994; Rodriguez et al., 2015). Mathematical models are very helpful in decision support systems, greenhouse climate control and prediction and planning of production (Heuvelink, 2018). There are many crop growth simulation models based explanatory process, some of them in photosynthesis and respiration, such as CROPGRO (Boote et al., 2012), TOMGRO (Dayan et al., 1993) and TOMSIM (Heuvelink, 1999) and other based on radiation use efficiency (*RUE*) of *PAR*, VegSyst (Gallardo et al., 2016), HortSyst (Martinez-Ruiz et al., 2019) and LINTUL3 (Shibu et al., 2010).

Macronutrients (N, P, K, Ca, Mg) uptake models along the life crop allow the optimization of fertilizers. The principal nutrient modeling is N since it is involved in the development of the foliar area and biomass production although all macronutrients are part of the essential nutrients. These elements are irreplaceable for a vital reaction or structure (Heuvelink, 2018).The models can be separated on explanatory (Roose et al., 2001), which considers diffusion and mass flow acting simultaneously to supply nutrients to the root sorbing surface (Rengel, 1993), and empirically (Juárez-Maldonado et al., 2017; Tei et al., 2002; Dugdale, 1967; Chin et al., 2011) as exponentials or polynomials models.

The HortSyst model (Martinez-Ruiz et al., 2019) is a discrete time dynamic model based on photothermal time index (Xu et al., 2010) to simulate leaf area index, as a rate of enzymatic reactions by Michaelis-Menten equation, biomass, utilizing

RUE intercepted and nitrogen uptake, as exponential model based on dry matter production rate.

The current work was developed during the vegetative phase of growth of tomato, where the shoot apical meristems forms metamers, consisting in an elongated internode, a leaf and bud, and then the shoot apical meristems are transformed into a inflorescence meristems (Heuvelink, 2018) so they will start the floral structures and later fruit, often depends on specific environmental and development signals (Lazar, 2003). It is during this phase that the tomato clusters will have the highest quality and yield are developed.

The objective of the current study is to extend the HortSyst model that describes the dynamics of photo-thermal time, total dry matter production, N uptake, leaf area index, and evapotranspiration for greenhouse crops, by updating model parameters and modifying the simulation time step. It was evaluated dry matter production with data coming from a new crop cycle with prunes, also the proposal of new macronutrients (N, P, K, Ca, Mg) models based in cumulative relative development rate (*RDRc*). Instead of basing nutrients estimations on dry matter production (*DMP*) because depending on the *DMP*, the parameters of N uptake model are rather sensitive to rate change of *DMP* so since this experiment was carried out with a better radiation condition improving the growth rate of *DMP*.

5.3. MATERIALS AND METHODS

5.3.1. The HortSyst model

HorSyst model was calibrated and evaluated using experimental data from a tomato crop (*Solanum lycopersicum* L., cv. Saladette), using temperature (°C) and solar global radiation (MJ m^{-2}) as input values, every 5 minutes inside the greenhouse. The experiment was carried out in 2018 in volcanic sand as substrate with a summer-fall growing season in a greenhouse. Detailed description of the Hortsyst model are available in Martínez et al. (2019).

The HortSyst model predicts in discrete time, crop biomass production (Eq. 2), nitrogen uptake, photo-thermal time (Eq. 1), evapotranspiration and leaf area index for greenhouse grown tomatoes. In this research it was calibrated and evaluated *DMP* changing the time measured for 5 min (i). Macronutrients uptake predictions in discrete time (Eq. 3) is the model proposed in the extended HortSyst model.

$$PTI(i+1) = PTI(i) + \Delta PTI \quad [1]$$

$$DMP(i+1) = DMP(i) + \Delta DMP \quad [2]$$

$$MN_{up}(i+1) = MN_{up}(i) + \Delta MN_{up} \quad [3]$$

Table 1. Parameters used for the extended HortSyst model

Output	Parameters	Symbol	Value	**Units**
DMP	Lower optimum temperature	T_{lo}	17	°C
	Upper optimum temperature	T_{uo}	23	°C
	Lower temperature	T_l	12	°C
	Upper temperature	T_u	33	°C
	Radiation use efficiency	RUE	5.89	g MJ^{-1} m^{-2}
PTI	Extinction coefficient	k	0.7	--
	Photothermal Index initial	PTI_i	0.0013	--
LAI	Slope of the curve	c_1	2.09E-04	--
	Intersection coefficient	c_2	0.0765	--

DMP: Dry matter production; *PTI*: photothermal time; *LAI*: leaf area index.

Table 2. Initial values measured for the extended HortSyst model

Parameters	Symbol	Value	**Units**
DMP initial	DMP_i	1.645	g m^{-2}
LAI initial	LAI_i	0.018	m^2 m^{-2}
Macronutrients initial uptake			
Nup initial	Nup_i	0.02	g m^{-2}
Pup initial	Pup_i	0.01	g m^{-2}
Kup initial	Kup_i	0.07	g m^{-2}
Caup initial	$Caup_i$	0.01	g m^{-2}
Mgup initial	$Mgup_i$	0.02	g m^{-2}

DMP: Dry matter production; *LAI*: leaf area index.

While in the original work HortSyst model (Martinez-Ruiz et al., 2019) the normalized thermal time was using like a daily average, in this version, the crop development was calculated as the relative development rate (*RDR*) as proposed by Soltani & Sinclair (2012) calculated each 5 min, insomuch as *RDR* use the daily average temperature. This modification calculates each 5 min, whether temperature is in the optimal range and only is obtainable 1 in a day if temperature is optimal throughout the day. This modification allows increasing the accuracy of the photo-thermal time (*PTI*) calculation.

$$RDR(i) = \begin{cases} 0 & if \quad (T_a \leq T_l) \\ \left(\frac{T_a - T_L}{T_{LO} - T_L}\right)/288 & if \quad (T_l < T_a < T_{lo}) \\ {}^{1}/_{288} & if \quad (T_{lo} \leq T_a \leq T_{uo}) \\ \left(\frac{T_U - T_a}{T_U - T_{uo}}\right)/288 & if \quad (T_{uo} < T_a < T_u) \\ 0 & if \quad (T_a \geq T_u) \end{cases} \qquad [4]$$

Model temperature parameters used for the HortSyst model was changed for T_l 12 °C, T_{lo} 17 °C, T_{uo} 23 °C, T_u 33°C T_a for actual temperature and following the recommendation where “tomato optimum growth occurs at 17–23°C and it stops at a maximum of 33°C and a minimum of 12°C" (Swiader et al., 1992, cited by Heuvelink, 2018), parameters used in Equation [4].

PAR interception was calculated each 5 min using values of f_{i-PAR} and the integral of *PAR* inside the greenhouse which was obtained from the product of the integral of accumulated solar radiation inside the greenhouse and the annual mean value of the ratio of *PAR*/*GSR* (global solar radiation) of 0.454 (Jacovides et al., 2003) given that there exist minor changes between the ratio of *PAR*/*GSR* inside plastic greenhouses and outside (Kittas et al., 1999).

$$PAR(i) = 0.454 * GSR(i) \qquad [5]$$

The intercepted radiation fraction was calculated assuming that attenuation of photosynthetic photon flux density through the canopy is following Beer's law by Monsi & Saeki (1953) calculating the proportion of incident *PAR* that is intercepted by the crop canopy analogous to Beer–Bouguer–Lambert Law (Sinclair, 2006).

$$f_{i-PAR}(i) = 1 - e^{-k*LAI(i)} \qquad [6]$$

Photothermal time (*PTI*) calculation is similar to the Hortsyst Model (Martinez-Ruiz et al., 2019) only adapted to a time of 5 min, instead of each hour. To estimate *PTI* initial (PTI_i) was necessary to express as exponential function *LAI* with domain in the number of measurements from sowing the seed to transplant, when it reached a *LAI* value of 0.019 starting from 0.

$$\Delta PTI(i) = RDR(i) * PAR(i) * f_{i-PAR}(i) \qquad [7]$$

Where the index *i* represents 5 min calculations.

Leaf area index (*LAI*) can be obtained by Michaelis-Menten equation because its dynamic approaches a rectangular hyperbola (Nelson et al., 2017), *PTI* acting as substrate concentration and c_1, c_2 as Michaelis constant linked to plant density, adding the value *LAI* removed for each prune expressed in Equation [8].

$$LAI(i) = \begin{cases} \frac{c_1 * PTI(i)}{c_2 + PTI(i)} * d \\ \frac{c_1 * PTI(i)}{c_2 + PTI(i)} * d - LAI_{PTL}(j) \quad for\ each \quad (pruned\ leaves) \end{cases} \qquad [8]$$

Dry matter production (*DMP*) in whole plant (leaf, stem, root and flower & fruit) was calculated using the model presented by Sinclair (1986) and actualized by Sinclair (2012).

$$\Delta DMP(i) = \begin{cases} RUE * f_{i-PAR}(i) * PAR(i) \\ RUE * f_{i-PAR}(i) * PAR(i) - DM_{PTL}(j) \quad for\ each \quad (pruned\ leaves) \\ RUE * f_{i-PAR}(i) * PAR(i) - DM_{PTS}(j) \quad for\ each \quad (pruned\ axillary\ buds) \end{cases} \qquad [9]$$

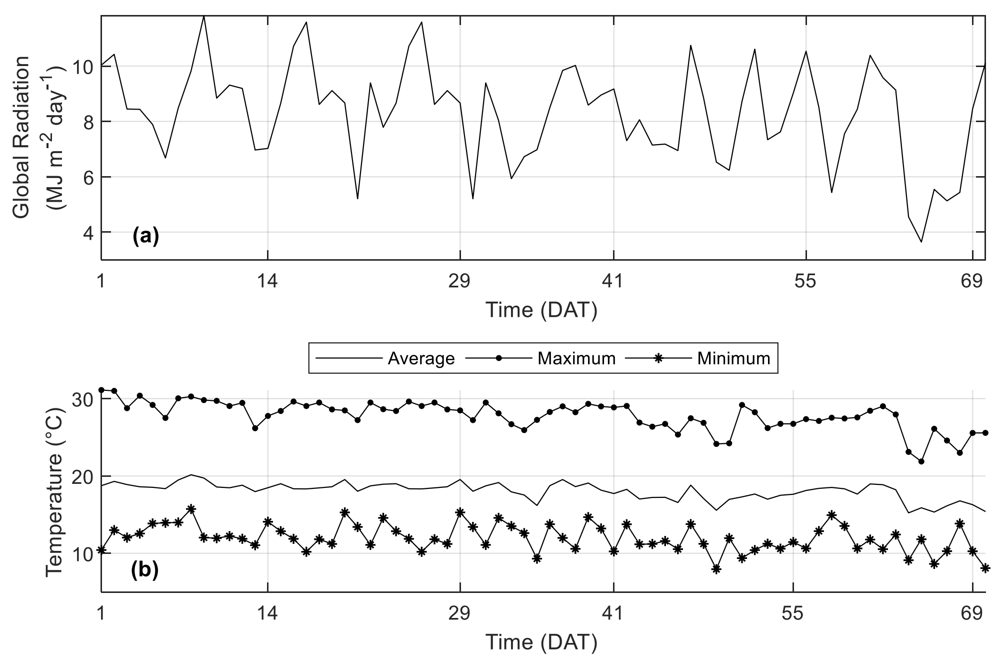
In order to maintain aeration between plants was necessary to prune old tomato leaves 51 and 55 days after transplant (*DAT)*, removing 0.26 and 0.82 *LAI* (Figure 2a). Model calibration was realized taking into consideration the *LAI* removed. Once a week were pruned axillary buds starting 19 *DAT* and ending with 8 prunes with a dry matter average of 1.43 g m^{-2} removed also was considering leaf prune 17.22 and 53.93 g m^{-2} (51 & 55 *DAT* respectively), showed in Figure 2a.

5.3.2. Site, experiments, and cropping details

The experimental work was carried out in plastic greenhouse condition with automated curtains and irrigation at Universidad Autónoma Chapingo, Chapingo, México. Geographical location: 19.487932 N, 98.887972 O and 2247 m elevation. Tomato (*Solanum lycopersicum* L., cv. Saladette) “PAIPAI F1” plants were grown in a hydroponic system using volcanic sand as substrate in bicolor bags (35x35cm white/black cal. 600). Seeds were sown on July 11 and seedling on August 15, 2018 with a duration of the experiment of 69 days after transplant (*DAT*). Nutrient solution was 12.56 meq NO_3^-, 1.6 meq $H_2PO_4^-$, 8.45 meq SO_4^{2-}, 7.81 meq K^+, 9.43 meq Ca^{2+}, 5.11 meq Mg^{2+}, 0.80 meq NH_4^+ (22.61 meq for anions and 23.14 meq for cations, water and fertilizers impurities were not considered) with 3 dS m^{-1} of electrical conductivity and pH 6 utilizing sulfuric acid (98%), 10 L of magnesium sulfate (2 g L^{-1}) was foliarly supplied weekly. Planting density was with 3.5 plants m^{-2} distributed in an area of 141.14 m^2 and a population of 494 tomato plants in 4 lines, selecting the 2 centrals to take completely random samples the days August 15 & 29, September 13 & 25 and October 9 & 23, 2018. The sample size was changing about the time because was necessary enough dry material for laboratory analysis, only for the first two samples were used 60 and 12 plants (1 & 14 *DAT*) divided into 4 groups then only 4 plants were necessary for each sample (29, 41, 55 & 69 *DAT*).

5.3.3. Environmental measurements

A CR1000 series data logger (Campbell Scientific, USA) was installed inside the greenhouse for the acquisition of data and all variables were measured in situ. Air temperature and humidity were measured using a CS215 (Campbell Scientific, USA) at 1.5 m of height and global radiation was measured using a pyranometer CMP 3 (Campbell Scientific, USA) at the same height of apical tomato bud (correcting the height weekly), both measurements were collected every 5 min (Figure 1).



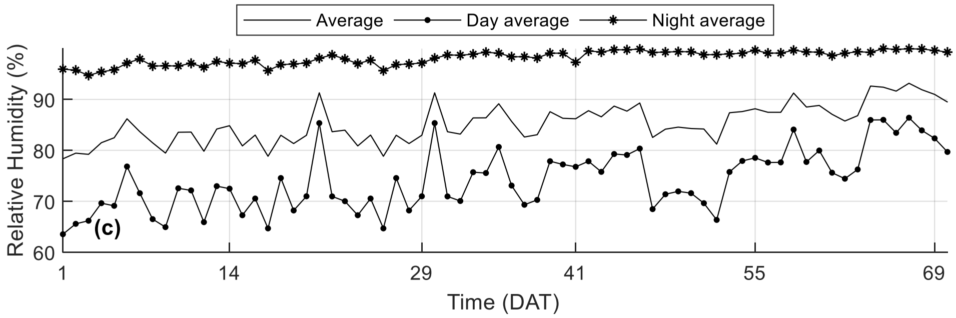


Figure 1. (a) Daily global radiation, (b) daily temperature average, maximum and minimum and (c) daily relative humidity average by day [>0 MJ m^{-2} $hour^{-1}$], night [=0 MJ m^{-2} $hour^{-1}$] and whole day, measured inside a greenhouse located in Chapingo, Mexico, during the 2018 autumn season.

5.3.4. Crop measurements

For each sampling the different parts of the tomato plant were separated in different organs: flower & fruit, leaf, stem and root. The first 2 sampling were separated in 4 groups (15 and 3 plants each group respectively) and the others by plant, all samples were analyzed in groups of 4. The leaf area was measured using an area meter (LI-COR, USA). Plants parts were dried at 70°C for 72 h. Macronutrients (N, P, K, Ca and Mg) content was measured following the method described by Pineda-Pineda (2011). Leaves and axillary buds pruned were used for macronutrients concentration measurements.

To obtain the average macronutrient concentration in the whole plant using its separated parts was used the pooled mean (*PM*).

$$PM_i = \frac{\sum_{e=1}^{s}(DM(e)*NC(n,e))}{\sum_{e=1}^{s}DM(e)} \qquad [10]$$

where *DM(e)* are the dry matter of tomato parts (flower & fruit, leaf, stem, root, pruned leaves and axillary buds), the number of organs involved (s) 4, 5 or 6, *NC(n,e)* is the nutrient concentration (*n*) N, P, K, Ca, Mg in a tomato part (*e*) and each sampling (*i*) 1, 14, 29, 41, 55 and 69 DAT. Only the biomass (e) present or removed until the corresponding sampling was considered.

Each pruned leaves and/or axillary buds were counted in the whole area of the experiment and biomass were calculated per plant or m^2.

5.3.5. Model Calibration

In order to fit model predictions to measurements the model was calibrated using the extended HortSyst model prodictions *DMP* and *LAI*, using the ordinary least squares (*OLS*) procedure (Wallach et al., 2019). The *OLS* parameters (θ) are the arguments of the model ($\hat{\theta}_{OLS}$) that minimize the sum of squared error (*SSE*) and residual variance ($\hat{\sigma}^2$ or RV) to know the uncertainty value. This was optimized utilizing the particle swarm solver from global optimization toolbox (MATLAB, 2018), selecting the best result in 20 runs, with a swarm size of 200.

$$\hat{\theta}_{OLS} = \underset{\theta}{argmin}\{\sum_{i=1}^{n}[y_i - f(x_i;\theta)]^2\} \quad [11]$$

$$\hat{\sigma}^2_{OLS} = \frac{\left\{\sum_{i=1}^{n}[y_i - f(x_i;\hat{\theta}_{OLS})]^2\right\}}{n-p} \quad [12]$$

where θ include are the parameters c_1 and c_2 to calibrate *LAI* (Equation [8]) and the parameter *RUE* to calibrate *DMP* (Equation [9]), x_i are the simulated output and y_i are the measurements in time *i*, *n* is the number of samples during the experiment period and *p* is the number of calibrated parameters

Macronutrients percent concentration of N, P, Ca and Mg were analyzed by fitting a two-term Gaussian model and percent concentration of K by fitting a polynomial curve of degree 4, minimizing the *SSE* by the method of nonlinear least squares and obtaining their coefficients of determination (R^2), using as input cumulative relative development rate (*RDRc*). The calculations and the graphical analysis were carried out using the curve fitting Toolbox 3.5.7 (MATLAB, 2018).

5.3.6. Model Evaluation

The performance of the non-calibrated and calibrated models of HortSyst *DMP* was evaluated by using the statistics model efficiency (*EF*), root mean squared error (*RMSE*) and residual variance (*RV*) (Wallach et al., 2019) and mean of standard squared deviations ($BIAS^2$), squared difference between standard deviations (*SDSD*) and lack of correlation weighted by the standard deviations

(*LCS*) statistics by Kobayashi & Salam (2000), same statistical indexes that were used to measure the performance of macronutrients uptake models (Nup, Pup, Kup, Caup and Mgup).

5.4. RESULTS AND DISCUSSION

The average day temperature was 21.37 °C and at night 14.9 °C, while average relative humidity was 69.69% during day and 97.2% at night, showing that the experiment was carried out in average in optimal temperature conditions during day but at night was 2.1°C below optimal conditions (17 to 23°C) (Swiader et al., 1992, cited by Heuvelink, 2018). The accumulated global solar radiation (*GSR*) intercepted in greenhouse for 69 *DAT* of the experiment was 641.44 MJ m^{-2} with a daily average of 9.29 MJ m^{-2} and outside of 17.13 MJ m^{-2}, These values were similar to the those reported by Matsumoto et al. (2014) of 18.01 MJ m^{-2} for Mexico City, where greenhouse plastic only allowed 54.2% to pass, less that reported by Zabeltitz (2011) between 55-70% for single covered greenhouse. A light requirement equal to or higher than 1 MJ m^{-2} day^{-1} natural *PAR* is reported for tomato culture (Heuvelink, 2018), that's means that 1.85 MJ m^{-2} day^{-1} of *GSR*, using the ratio of *PAR*/*GSR* (0.54) (Jacovides et al., 2003), or more is necessary in producing greenhouse tomatoes.

The *LAI* measurements show a behavior of a convex upward function for the vegetative growth (Figure 2a) same behavior as the results of Boote et al. (2012), Campillo et al. (2010) and Martinez-Ruiz et al. (2019). The residual plot (Figure 2b) shows two behaviors, the first three measurement shows an increasing underestimation and the next two shows an overestimation and the last one shows an underestimation again. An adjusted *LAI* is required to calculate *DMP* (Equation [9]), resulting with an efficiency (*EF*) of 0.99 (Table 4). The residual plot of *LAI* simulation showed a highly error allocated in 29 *DAT* (Figure 2c) same date as the beginning of fruit development.

DMP calibration simulation (Figure 3a & 3b) contain the parameter *RUE* obtained by Gallardo et al. (2014) and Martinez-Ruiz et al. (2019) to compare results, it was used the production by g m^{-2} (Figure 3a), both underestimated the measurements but insomuch as the *RUE* obtained for different authors was development under different plant densities (2 & 3.5 plants m^{-2}, respectively), the way to compare this parameter is in g $plant^{-1}$ (Figure 3b), so Gallardo et al. (2014) overestimate and Martinez-Ruiz et al. (2019) underestimate the measurements. Simulation failed to predict the last two measurements (Figure 2c) at the moment of fruit development, Gallardo et al. (2011) used two values of *RUE*, one for vegetative period and the other for reproductive growth to simulate muskmelon.

Table 3. Dry matter content (*DMC*) and leaf area index (*LAI*) average measurements

	Days after transplant (DAT)					
	1	**14**	**29**	**41**	**55**	**69**
LAI **[m^2 m^{-2}]**	0.019 (5.7e-04)	0.187 (0.013)	1.06 (0.091)	1.984 (0.142)	2.878 (0.29)	5.538 (0.48)
DMC **[g m^{-2}]**	1.63 (0.026)	10.34 (0.25)	90.88 (3.9)	251.6 (2.6)	400.07 (9.14)	733.08 (10.9)

Between brackets the standard deviation

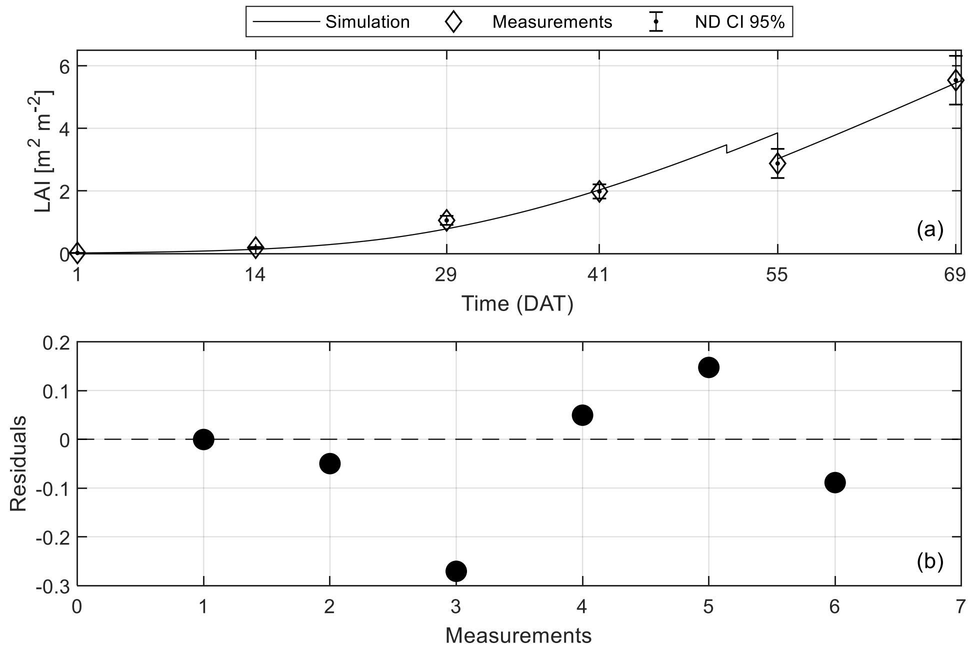


Figure 2. a) Time course of simulated and measured values of leaf area index (*LAI*), with a confidence intervals (IC) for normal distribution (ND) of the measurements b) Residual plot of *LAI* simulation*.*

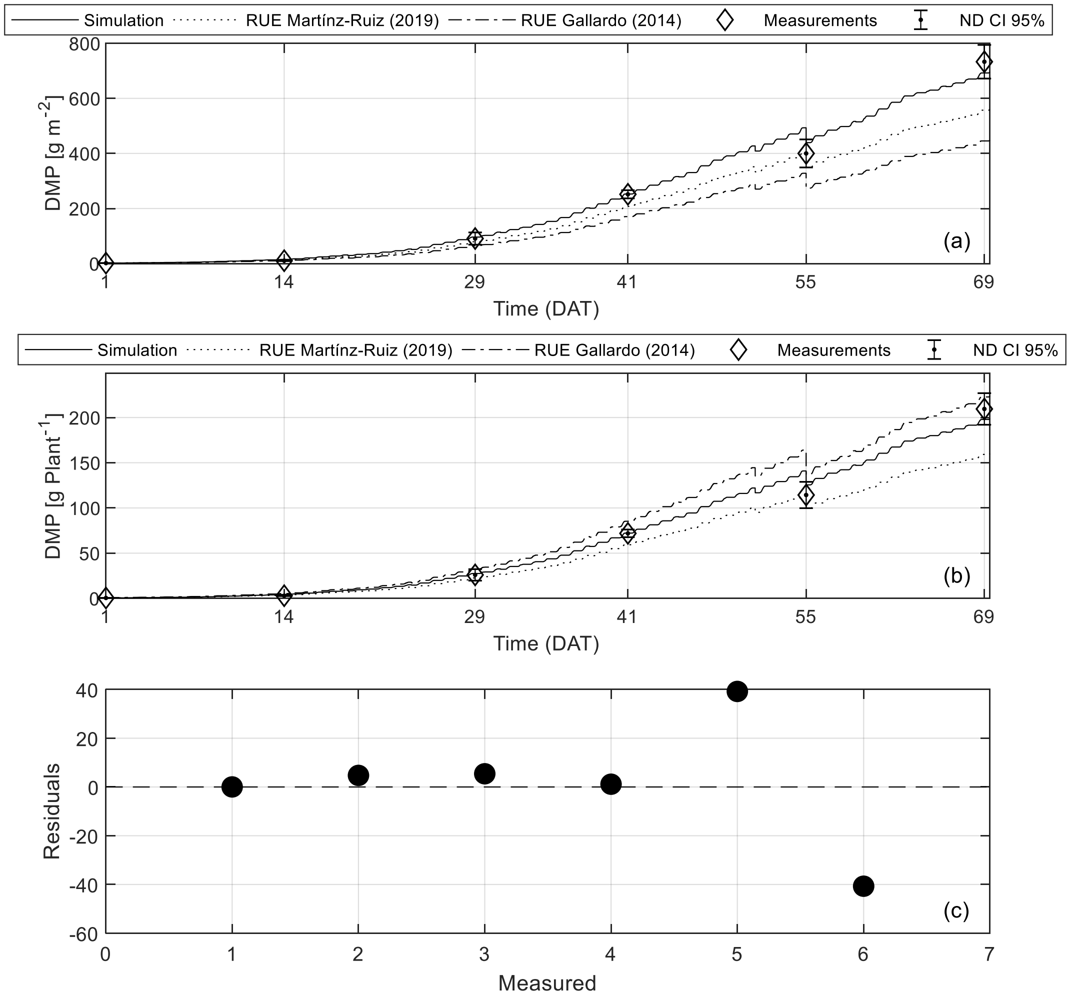


Figure 3. a) Time course of simulated with calibrated *RUE*, Martinez-Ruiz *RUE* and Gallardo *RUE* and measured values of dry matter production (*DMP*) by m^2 and b) Time course of DMP simulated by plant; with a confidence intervals (IC) for normal distribution (ND) of the measurements, c) Residual plot of *DMP* simulation by m^2.

5.4.1. Evaluation of the HortSyst model

All the calibration parameters (*RUE*, c_1 and c_2) determined for tomato crop are listed in Table 4, these parameters were obtained from experimental data (Table 3) and was evaluated the parameter of *RUE* obtained by Martinez-Ruiz et al. (2019). The optimized value of *RUE* obtained from data of *PAR* interception and *DMP* was 5.89 g MJ^{-1} m^{-2} (1.68 g MJ^{-1} $plant^{-1}$) and the optimized value of c_1 and c_2 obtained from data of *RDR* and *PAR* interception was 2.0855e-04 and 0.0765 respectively using a PTI_i estimated in 0.0013. In contrast, others researchers that have modeled *DMP* as a function of *PAR* intercepted have reported a *RUE* of 3.3-3.5 g MJ^{-1} $Plant^{-1}$ in modern greenhouse (Heuvelink, 2018), 1.16 g MJ^{-1} $Plant^{-1}$ in a nitrogen study (Elia & Conversa, 2012) and in a conventional cropping system 1.3 g MJ^{-1} $Plant^{-1}$ (Ronga et al., 2017).

It's not possible to compare *LAI* models (Table 4) because worked in different time scales (5 min and 1 h) and the parameters of *LAI* model works like a reaction rate in Michaelis-Menten equation, so to compare *DMP* models was used the same *LAI* model calibrated, this is possible given that *DMP* model can work in both times.

Table 4. Summary of statistical indexes used to calibrate and evaluate the performance of the HortSyst and extended model simulated for *DMP* and *LAI*.

	Non-Calibrated	**Calibrated**	
	DMP	*DMP*	*LAI*
RUE	4.86	5.89	c_1 2.1706e-04 c_2 0.0837
	Evaluation	**Calibration**	
SSE	35676.9	3246.1	0.1
EF	0.91	0.99	0.99
RV	8919.2	811.5	0.02
MSE	5946.1	541	0.012
RMSE	77.1	23.2	0.13
$BIAS^2$	2186.2 (37%)	2.7 (0.5%)	0.00 (0%)
SDSD	3461.6 (58%)	86.4 (16%)	0.00 (0%)
LCS	298.2 (5%)	451.9 (83.5%)	0.02 (100%)

SSE of *DMP* evaluated and calibrated HortSyst extended model have the error allocated in a bigger proportion in the last two measurements (Figure 3c). Error distribution of $BIAS^2$, *SDSD* and *LCS* was ranked in order to their *MSE* percentual participation (Table 4). The error of *$BIAS^2$* and *SDSD* was almost null in LAI simulation and in DMP and LAI simulation *LCS* was the one who participated most in the *MSE* (Table 4), this means that the calibrated model failed to simulate the pattern of the fluctuation across the measurements while HortSyst model failed to simulate the magnitude of the fluctuation between the measurements and have higher average standard deviation (*$BIAS^2$*).

Table 5. Macronutrients concentration (%) average measurements

	Days after transplant					
Macronutrients	1	14	29	41	55	69
N	1.35 (0.15)	3.87 (0.19)	2.02 (0.30)	1.90 (0.24)	1.99 (0.14)	2.00 (0.22)
P	0.63 (0.03)	0.98 (0.02)	0.84 (0.11)	0.64 (0.10)	0.69 (0.03)	0.67 (0.06)
K	4.20 (0.49)	4.60 (0.47)	4.66 (0.35)	4.30 (0.50)	4.55 (0.43)	3.66 (0.23)
Ca	0.89 (0.20)	2.01 (0.51)	1.29 (0.23)	1.19 (0.22)	1.16 (0.23)	0.53 (0.07)
Mg	0.96 (0.14)	1.84 (0.06)	1.79 (0.18)	1.80 (0.20)	1.70 (0.13)	0.93 (0.17)

Between brackets the standard deviation

5.4.2. Macronutrients Models

5.4.2.1. Macronutrients concentration models

The macronutrients concentrations were obtained from laboratory results (Table 5), this concentration change by the state of development of the tomato crop (Figure 4).

Two-term Gaussian model

$$\%Nut(i) = a1 * e^{\left(-\left(\frac{RDRc(i)-b1}{c1}\right)^2\right)} + a2 * e^{\left(-\left(\frac{RDRc(i)-b2}{c2}\right)^2\right)} \quad [13]$$

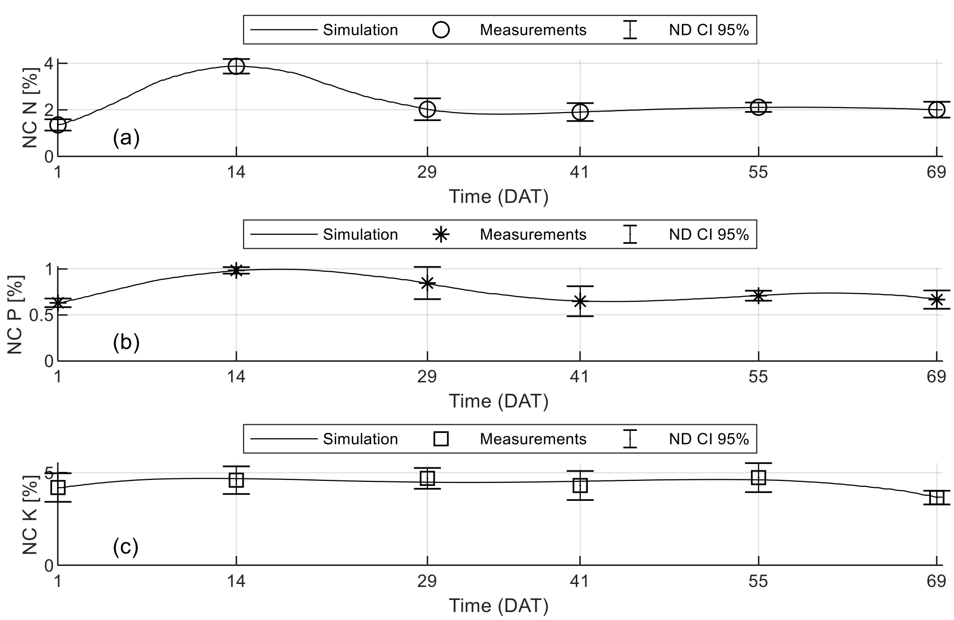
Polynomial curve of degree 4

$$\%K(i) = p1 * RDRc(i)^4 + p2 * RDRc(i)^3 + p3 * RDRc(i)^2 + p4 * RDRc(i) + p5 \quad [14]$$

To calculated the nutrient concentration (Equation [13], N, P, Ca and Mg) and (Equation [14], K) were utilized the parameters of table 6 and the relative development rate cumulative as input.

Table 6 Parameters and goodness of fit of the nutrients of two-term Gaussian model and polynomial curve of degree 4

Two-term Gaussian model								
							Goodness of fit	
Parameter	**a1**	**b2**	**c3**	**a2**	**b2**	**c3**	***SSE***	***R^2***
Nutrients								
N	3	9.539	8.695	2.107	40.38	32.47	3.126e-13	0.99
P	0.9867	12.1	18.05	0.688	44.24	14.97	6.128e-13	0.99
Ca	1.999	10.81	12	1.345	36.02	12.2	6.895e-16	0.99
Mg	1.772	11.54	14.67	1.712	36.13	14.87	1.723e-18	0.99
Polynomial curve of degree 4								
Parameter	**p1**	**p2**	**p3**	**p4**	**p5**			
Nutrient								
K	-4.969e-06	0.0004531	-0.01357	0.1456	4.183		0.1145	0.86



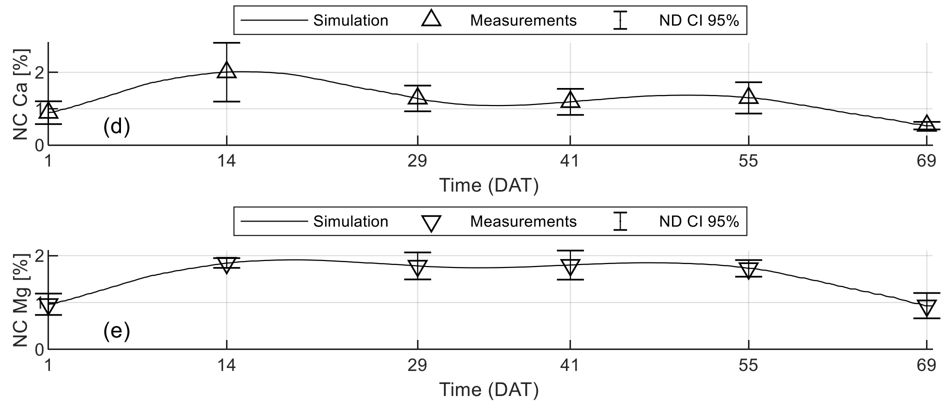


Figure 4. Nutrients concentration (NC) models, measurements and confidence intervals (IC) for normal distribution (ND) of Nitrogen (a), Phosphorus (b), Potassium (c), Calcium (d) and Magnesium (e).

Macronutrients concentration at the end of the experiment were at 69 *DAT* N (2%), P (0.67%), K (3.66%), Ca (0.53%), Mg (0.93%), reaching its peak at 14 DAT N (3.87%), P (0.98%), K (4.6%), Ca (2.01%) and Mg (1.84%), table 5. Other authors have reported similar results as N (~2%), K (~5%) and P, Ca, Mg (0.1-1%) in general plants (Barker & Pilbeam, 2015), N (2.57-5.77%), P (0.51-0.55%), K (2.67-4.76%), Ca (2.26-2.59%) and Mg (1.66-2.33%) (Pineda-Pineda, 2011) and N (1.65-4.5%), P (0.2-0.48%), K (2.51-5.33%), Ca (0.75-2.4%) and Mg (0.6-0.83%) (Bertsh, 2003), average of all parts of the plant throughout the tomato cycle crop.

Figure 4 showed the nutrients concentration but also is an indirect way to see de nutrient uptake critical points leaving aside P, K, Ca and Mg, there is a remarkable point in the development of nitrogen concentration 14 *DAT*, it’s of special interest since there is a relationship between N in plant (Figure 4a) and its rate of growth or *DMP*, if N supply to a plant is interrupted, the plant N concentration decrease, and growth rate slows (Barker & Pilbeam, 2015). Since the amount of dry matter production (*DMP*) is proportional to *PAR* intercepted (Equation [9]) and leaf nitrogen and leaf photosynthetic capacity are strongly correlated (Heuvelink, 2018) providing crops with enough N to development and maintain a large leaf, in a critical point as vegetative growth (future production potential), it is necessary to maximize the interception of *PAR* radiation.

Same as nitrogen, phosphorus (Figure 4b) has a pike 14 *DAT* (0.98%), since the central role of P in plants is in bioenergetic used in photosynthesis (Barker & Pilbeam, 2015), it implies that P was highly demanded by plant as N to form biomass.

Potassium have many principal roles in physiological, biochemical process. “Lessen plant stresses to abiotic and biotic factors, regulate osmotic pressure, reduce plant lodging, and improve fruit quality” (Barker & Pilbeam, 2015), resulting in almost a constant requirement along vegetative growth (Figure 4c).

Calcium and magnesium are involved in cell structure and equal to N and P, they reached their slight peaks concentration (Figure 4d and 4e) at 14 *DAT*.

The nutrients concentrations ratios are not constant for the growing vegetative period, similar conclusion from Knecht & Goransson (2004).

5.4.2.2. Macronutrients uptake model

The macronutrient concentrations allow to know the amount of macronutrient uptake (MN_{up}) from biomass (*DMP*) in time (*i*), each 5 min.

$$MN_{up}(i) = DMP(i) * (\%Nut(i)\ or\ \%K(i)) \qquad [15]$$

Where the nutrient concentration can be from equation [13] or [14], multiplying *DMP* in time (*i*), each 5 min.

Table 7. Macronutrients uptake (g m-2) average measurements

	Days after transplant					
Macronutrients	1	14	29	41	55	69
N	0.02 (1e-03)	0.4 (0.05)	1.88 (0.17)	4.84 (0.72)	9.96 (0.70)	14.66 (0.84)
P	0.01 (5e-04)	0.1 (0.01)	0.8 (0.16)	1.64 (0.27)	3.35 (0.29)	4.89 (0.34)
K	0.07 (0.01)	0.47 (0.06)	4.41 (0.50)	10.94 (1.01)	22.48 (3.25)	26.88 (0.54)
Ca	0.01 (1e-03)	0.21 (0.07)	1.22 (0.33)	3.02 (0.62)	6.11 (1.18)	3.91 (0.66)
Mg	0.02 (2e-03)	0.19 (0.02)	1.66 (0.15)	4.59 (0.66)	8.20 (1.06)	6.91 (1.58)

Between brackets the standard deviation

Table 8. Summary of statistical indexes of macronutrients uptake models

Models	**Nup**	**Pup**	**Kup**	**Caup**	**Mgup**
SSE	1.30	0.14	3.65	0.38	0.66
EF	0.99	0.99	0.99	0.98	0.99
RV	0.32	0.03	0.91	0.09	0.16
MSE	0.22	0.02	0.61	0.06	0.11
RMSE	0.47	0.15	0.78	0.25	0.33
BIAS²	0.00 (0%)	0.00 (0%)	0.03 (5%)	0.01 (14%)	0.00 (0%)
SDSD	0.03 (14%)	0.00 (0%)	0.03 (5%)	0.01 (14%)	0.00 (0%)
LCS	0.18 (86%)	0.02 (100%)	0.55 (90%)	0.05 (71%)	0.10 (100%)

The macronutrients uptake models got an EF higher that 0.98 and the error of simulation is due to LCS, implying that the model fault in the fluctuation pattern, although it is almost null.

The macronutrients uptake has a dynamic growth except for Ca and Mg, where they are reduced to 69 DAT in concentration (Figure 7) and macronutrients uptake (Figure 8), this is due to pruning performed at 55 DAT. These measures help us to know the amount needed to keep a tomato crop in optimal conditions with the use of fertilizers.

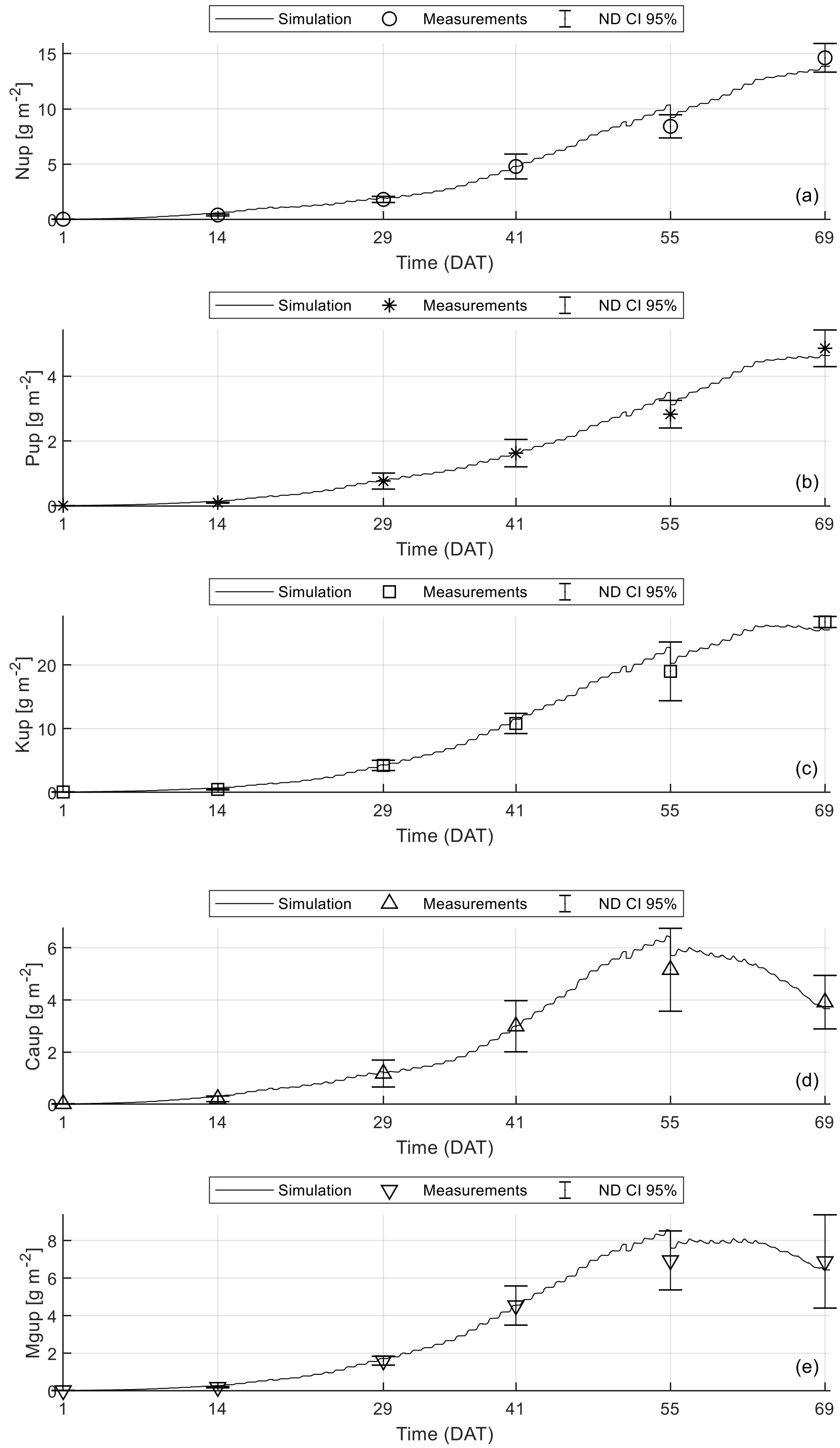


Figure 5. Macronutrients uptake measurements and confidence intervals (IC) for normal distribution (ND) of Nitrogen-Nup (a), Phosphorus-Pup (b), Potassium-Kup (c), Calcium-Caup (d) and Magnesium-Mgup (e).

5.5. CONCLUSIONS

LAI measured and simulated showed that exist a different rate at the beginning of fruit development (29 DAT), that try to fit again with the simulation on the last measurements. Indicating that there is a period of adaptation of the *LAI* growth rate when the fruit development starts.

HortSyst model achieved an *EF* of 0.91 in *DMP* simulating, although it obtained an *RV* 10 times higher than the obteined by the HortSyst model extended, this may be due to environmental conditions where the model was generared and calibrated, with a special emphasis in its global radiaton of mean 3.99 MJ m^{-2} d^{-1} (Martinez-Ruiz et al., 2019) againts 9.27 MJ m^{-2} d^{-1} in this experiment. Only the parameter *RUE* can change the error allocate in the simulation between *SDSD* on HortSyst model and *LCS* on the extended model that have to do with the magnitude and fluctuation pattern of the simulation respectively, due to the direct relationship between the biomass produced and the intercepted radiation, when the error of the parameter of the *RUE* is minimized, the magnitude in the simulation is diminished and the error is focused in the fluctuation of the simulation.

The last two measurements values of DMP show that the value of RUE is not unique throughout the crop cycle and given that one value underestimates and the other underestimates is not constant and this may be due to the development of the fruit.

Only K concentration model was not adjusted with two term gaussian model this may be due to the measured values in laboratory where obtained the highest standard deviation values among the macronutrients, so it is not ruled out that all the macronutrients analyzed can fit that gaussian model.

Tomato plant growth has a critical point around 14 *DAT* where macronutrients are demanded in a higest proportional rate just before fruit develoment, showing the importance of the first days of development after transplantation.

Altougth exist an relationship between N uptake and *DMP* (Barker & Pilbeam, 2015) if the growth rate changes, as it was in this experiment, the calibrated parameters for all macronutrients uptake are readjusted so macronutrients uptake model only works correctly if abiotic condition are mantained.

Macronutrients models work with temperatures inputs and growing optimal temperatures parametres from tomato as relative development rate accumulated then it does not depend on the growth rate but on the temperatures present during tomato development.

5.6. LITERATURE CITED

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