UNIVERSIDAD AUTÓNOMA CHAPINGO

POSGRADO EN INGENIERÍA AGRÍCOLA Y USO INTEGRAL DEL AGUA

DEVELOPMENT, ANALYSIS AND EVALUATION OF A DYNAMIC MODEL OF GROWTH, TRANSPIRATION AND NITROGEN UPTAKE FOR TOMATOES IN GREENHOUSES

THESIS

THAT AS A PARTIAL REQUIREMENT

FOR DEGREE OF:

DOCTOR IN AGRICULTURAL ENGINEERING AND INTEGRATED WATER USE

PRESENT:

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Chapingo, México. October 2017

DEVELOPMENT, ANALYSIS AND EVALUATION OF A DYNAMIC MODEL OF GROWTH, TRANSPIRATION AND NITROGEN UPTAKE FOR TOMATOES IN GREENHOUSES

Tesis realizada por el M.I. ANTONIO MARTINEZ RUIZ bajo la supervisión del comité asesor indicado, aprobada por el mismo y aceptada como requisito parcial para obtener el grado de:

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ACKNOWLEDGEMENTS

To Universidad Autónoma Chapingo for all the academic training received, and to all the academic and administrative staff.

To the Consejo Nacional de Ciencia y Tecnología (CONACYT), for the economic support that was given to me during the Ph.D education studying.

To the Posgrado en Ingeniería agrícola y Uso Integral del Agua by scientific and technological training provided and the support given to the successful completion of this training cycle.

To my advisor committee

- Dr. Irineo L. López Cruz who with wise leadership direction of this research and the revisions and corrections of the scientific articles.
- Dr. Joel Pineda Pineda for his valuable comments and suggestions and Support in the laboratory analysis and revision of the articles.
- Dr. Agustin Ruiz García for his valuable contribution and support in the accomplishment for this work of research during the doctorate.
- Dr. Gabino Alberto Martínez Gutiérrez for having accepted to review this work.
- Dr. Mauricio Carrillo Garcia for the support, that through the IAUIA provided me to carry out the experiments to culminate this work
- Dr. Jorge Victor Prado Hernández for the support, advice and suggestions during the experiments.

To God for allowing me to reach this goal

DEDICATION

To my wife Dulce Sandra Garcia José and to my dear son Santiago Antonio Martinez García.

To all my brothers, my sister and my mother.

To the teacher Rosalba Julian Bolaños and her husband Arturo Jiménez José

To all my Friends

DEVELOPMENT, ANALYSIS AND EVALUATION OF A DYNAMIC MODEL OF GROWTH, TRANSPIRATION AND NITROGEN UPTAKE FOR TOMATO IN GREENHOUSE

DESARROLLO, ANÁLISIS Y EVALUACIÓN DE UN MODELO DINÁMICO DE CRECIMIENTO, TRANSPIRACIÓN Y ABSORCIÓN DE NITROGENO PARA JITOMATE EN INVERNADERO.

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RESUMEN

El modelo HortSyst es un modelo en tiempo discreto para describir la dinámica del tiempo fototérmico (PTI), producción de materia seca (DMP), nitrógeno absorbido (Nup), índice de área foliar (LAI) y la transpiración del cultivo (ETc) para cultivos en invernadero. El modelo asume que no existen limitaciones de agua y nutrimentos. Las variables de entrada son la temperatura del aire, humedad relativa, y la radiación global solar diaria. Este modelo cuenta con trece parámetros. Para evaluar la predicción del modelo, se llevaron a cabo dos experimentos en invernadero, durante otoño-invierno y primavera-verano en Chapingo México. Se trabajó con dos cultivos de jitomate (*Solanum lycopersicom L.*) variedad “CID F1” en sistemas hidropónicos. Las plantas se distribuyeron con densidad de 3.5 plantas m^{-2}. El objetivo de esta investigación fue desarrollar un modelo de cultivo y adaptarlo a invernaderos mexicanos y comparar el rendimiento de este modelo HortSyst con el modelo Vegsyst, también se llevó a cabo un análisis de sensibilidad global usando el método de Sobol para determinar cuáles parámetros fueron más importantes y después se realizó una calibración para encontrar los valores correctos de los parámetros, se usó el método de mínimos cuadrados no lineales y un método heurístico (evolución diferencial), también se llevó a cabo un análisis de incertidumbre para cuantificar la incertidumbre de las predicciones del modelo para ello se aplicó un método frecuentista y el método GLUE. Finalmente, se presentó una propuesta para el uso del modelo HortSyst para el manejo del riego y nitrógeno para jitomate en cultivo sin suelo. Se usaron diferentes estadísticas para juzgar la efectividad del modelo por ejemplo; la raíz del cuadrado medio del error (RMSE), sesgo, la eficiencia de modelación (EF), coeficiente de variación (CV), kurtosis, skewness, etc. el análisis y evaluación del modelo fue exitoso y las estadísticas resultaron aceptablemente. En conclusión el modelo podría ser una buena herramienta para el manejo de los sistemas de producción en invernadero.

Palabras claves: Modelos de simulación, absorción de agua, expansión de área foliar, curva de dilución.

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2. Director de la tesis

ABSTRACT

The HortSyst model is a new discrete time model for describing the dynamics of photo-thermal time (PTI), dry matter production (DMP), N uptake (Nup), leaf area index (LAI), and the crop transpiration (ETc) of greenhouse crops. The model assumes that crops have no water and nutrient limitations. The input variables are air temperature, relative humidity, and daily solar global radiation. HortSyst has a total of thirteen parameters. In order to test model predictions, two experiments were carried out under greenhouse conditions, during the autumn-winter and spring-summer season, in Chapingo, Mexico. Two tomato (*Solanum lycopersicom L.*) cultivar "CID F1" crops were grown in hydroponic systems. Plants were distributed with a density of 3.5 plants m^{-2}. The aim of this research was to develop a new crop model and adapt it to Mexican greenhouses, and compare the performance of the HortSyst with the VegSyst one. In addition a global sensitivity analysis was carried out with Sobol method to determine which parameters were more important and then a calibration was run to find the correct values of these parameters using the nonlinear least square method and a heuristic method (differential evolution). Also, an uncertainty analysis was conducted to quantify the uncertainty of the model prediction; for this a, Frequentist method and the Bayesian method called Generalized Likelihood Uncertainty Estimation methods were applied. Finally, a proposal was presented for using the HortSyst model was given for the irrigation and nitrogen management of tomatoes in soilless culture. Different Statistics were used to assess the effectiveness of the model, such as Root Mean Square Error (RMSE), bias, modeling efficiency (EF), the coefficient of variance (CV), Kurtosis, Skewness, etc. The analysis and evaluation of the model were successful and all the statistics proved acceptable. In conclusion, this model could be a good tool for the management of greenhouse production systems.

Keywords: simulation models, water uptake, leaf area expansion, dilution curve

1. GENERAL INTRODUCTION

In a crop, growth is characterized by the processes of capture and use of solar radiation, carbon dioxide, water and nutrients to accumulate dry matter or biomass. Therefore, growth models have a module that calculates the production of structural biomass according to the captured carbon dioxide, the use of solar radiation, and / or the transpired water. The phenological development of the crop is mainly represented by the air temperature (Bechini et al., 2006), usually represented as degrees days or thermal time (° C d), a process that is linked to the development of the leaf area, responsible for capturing solar radiation, CO_2 and transpiration.The growth of the crop is then driven by the net accumulation of carbon, assimilated by the leaves and transformed into biomass. Biomass is distributed differentially between plant organs (leaves, roots, stems and fruits), taking into account the losses by respiration, coupled with the phenological development and the availability of water and nutrients captured from the ground by the roots. While the leaves assimilate carbon, they also lose water by transpiration. Crop models can be explanatory or descriptive. Explanatory models simulate a feature (crop growth) in terms of processes that occur at hierarchical scales (leaf photosynthesis).

Descriptive models show the existence of relationships between elements of a system (interception of light and dry matter production or use of water and dry matter production) but do not provide a more detailed explanation (Van Ittersum et al., 2003). Therefore, crop growth modeling can be done by following three approaches depending on the hierarchy of processes and the scales involved: a) The path of carbon assimilation, b) The solar radiation approach (efficiency of use of radiation, RUE), c) The transpiration approach (water use efficiency, WUE).

The crop models are complex dynamic models that simulate the growth and development, considering biophysical and primary biochemical processes in the soil-crop-atmosphere system, such as photosynthesis, respiration, transpiration, dry matter distribution, and senescence (Wang et al., 2013). These models are

valuable tools for crop management such as irrigation and nutrition. They allow understanding and predicting complex crop responses to the effects of agricultural practices, environmental conditions and crop characteristics to improve production. Therefore, they play an important role in crop monitoring, yield prediction, field management recommendations, evaluation of potential production, and assessment of the impact of climate change. In addition to increasing interest in optimal control for greenhouse environments (Van Straten et al., 2010). A cropping system model is a technology for systematized analysis, numerical simulation, and quantitative expression of the dynamic processes of growth and development of the main crops and the influence of environmental factors in these processes with information technology (Arnott and Pervan, 2005; Wenjia and Hao, 2012), which allows the analysis of processes considering the influence of multiple factors (Shi et al. al., 2015). Van Straten (2008) defines a model as a simplified representation of reality that encapsulates the significant aspects of the real system for the intend purpose it is seen as a mathematical equations, to restrict the space of possible outcomes.
Because of the increasing areas under irrigation and the high water requirements of crops (which consume around 70% of water available to human beings). The scarcity of water resources is leading to increasing controversy about the use of water resources by agriculture and industry, for direct human consumption, and for other purposes. Such debate could be alleviated by improving crop water use efficiency, so that increasing water use efficiency of crops is becoming a main goal for agriculture and food security goals. From the point of view of agricultural productivity, mineral nutrition is the second factor that limits crop growth after water availability, therefore, high amounts of fertilizer are required to produce large amounts of biomass (Le Bot et al., 1998). There are several approaches that differ in the degree of detail to model nitrogen in the soil and its limitation to crop growth, we distinguish between basically static approaches and the understanding of the dynamic approach of nitrogen. The effect of nitrogen status on phenology and on phenological processes is expressed as the difference between optimal nitrogen and actual concentration

in tissues (Van Ittersum et al., 2003). The prerequisites for crop management models are the ability to predict soil water and nutrient transport, root uptake, nitrogen transformations, dry matter production and distribution, and to describe physiological phenomena such as fruiting and ripening (Bar-Yosef and Klaering, 2012). There is an intimate relationship between the state of nitrogen (N) and phosphorus (p) and carbon metabolism. The plants optimize the carbon gained, in relation to the nitrogen available for photosynthesis, this implies the close relationship between the nitrogen concentration in the leaves and the maximum photosynthetic activity measured at saturated light intensities, under optimum temperature, and humidity at environmental CO_2 levels. All these considerations are necessary to represent and express these interactions through mathematical equations through modeling that could be a good tool for the management with high efficiency to avoid the wast of water and provide the irrigation according to the demand of the plant, especially in for soilless culture where water retention of a substrate is too low and the irrigation programming play an important role in the production systems. The efficiency term is also applied for nutrient management with the goal of reduce the impact in the aquifer pollution and reduce the production cost in greenhouses. So its important propose solution to this problem and help to growers to take decision to improve the efficiency in this system.

A mathematical model consists of state variables, output and input variables (measurements, parameters, and initial conditions). These models can have up to 200 parameters or more, which must be estimated with experimental data, so the acquisition of the values of certain parameters is difficult as they can vary according to environmental conditions, cultivar, seasonal variations and other factors (Confalonieri et al., 2010; Ceglar et al., 2011; Wang et al., 2013). As the number of parameters increases, uncertainty in model prediction due to uncertainty in input variables becomes more important. In such situations it is necessary to determine the domain of such parameters (Cooman and Schrevens, 2006). Sensitivity analysis is the first step in clarifying the importance of these (Cooman and Schrevens, 2007). Therefore, the sensitivity analysis evaluates the relative importance of input variables as well as their evolution over time of output and state variables (Saltelli et al., 2008). The estimation of these parameters is another important requirement because the behavior of the model depends to a large extent on the accuracy with which they were estimated. The predictions obtained by the models are not reliable and unrealistic when using parameter values that are not correct (Makowski et al., 2006; Wang et al., 2013) and are intended to apply to different conditions. Once a model is available and its parameters were estimated, it must put to test by checking its performance on a set of independent data, not used before. This process is known as model validation. Another important element in the modeling process is uncertainty. Uncertainty is one of the most inherent and prevalent properties of knowledge arising from lack of information, imprecision and approximations of models made for reasons of simplicity. It would not be exaggerated to say that real world decisions that do not involve uncertainty do not exist or belong to a truly limited class (Druzdzel and Flynn, 2002). Due to all this, it is important to carry out an uncertainty analysis on a model when it will be integrated into a decision support system (DSS) for the management of a production system (Gupta et al., 2010) such as irrigation management (Giusti and Marsili, 2015) and crops nutrition (Anastasiou et al., 2005) and increase the effectiveness of management knowledge through the use of DSSs (Refsgaard et al., 2007). Some DSSs developed for models of crops in greenhouses are; HORTISIM (Cohen & Gijzen, 1998), TOMGRO (Sauviller et al., 2001), VEGSYST developed by (Gallardo et al., 2014; Granados et al., 2013) for the management and supplying of Nitrogen ad Irrigation scheduling for crops in greenhouse.

The objectives of this research were to develop a dynamic growth model (HORTSYST) for cultivation under soilless culture in greenhouses, for the prediction of pho-thermal time, dry matter production, Nitrogen uptake, leaf area index, and transpiration of the crop to be integrated into a decision support system. In addition, a sub-model for the calculation of leaf area index is presented, based on a new concept called photo-thermal time, which couples the effect of temperature, global solar radiation on crop growth and development, once the mathematical structure of the model was proposed it was carried out a global sensitivity analysis to determine the parameters that have the most influence on the uncertainty of the model, and subsequently a local and global calibration were run of the parameters selected from the results of the sensitivity analysis, because this model will be integrate into a decision support system, it was convenient to carry out an uncertainty analysis using a frequentist method and a Bayesian approach (GLUE) to determine the uncertainty of the output variables caused by the perturbation of the parameters, in order to quantify the predictive quality of the HortSyst model in different scenarios. Finally, a proposal was made for the use of the model in the irrigations scheduling and programming of the nitrogen dosage for a hydroponic tomato crop. All of the modeling process described above are summarized in Figure 1, which shows the complete schematic of the steps involving a complex modeling process.

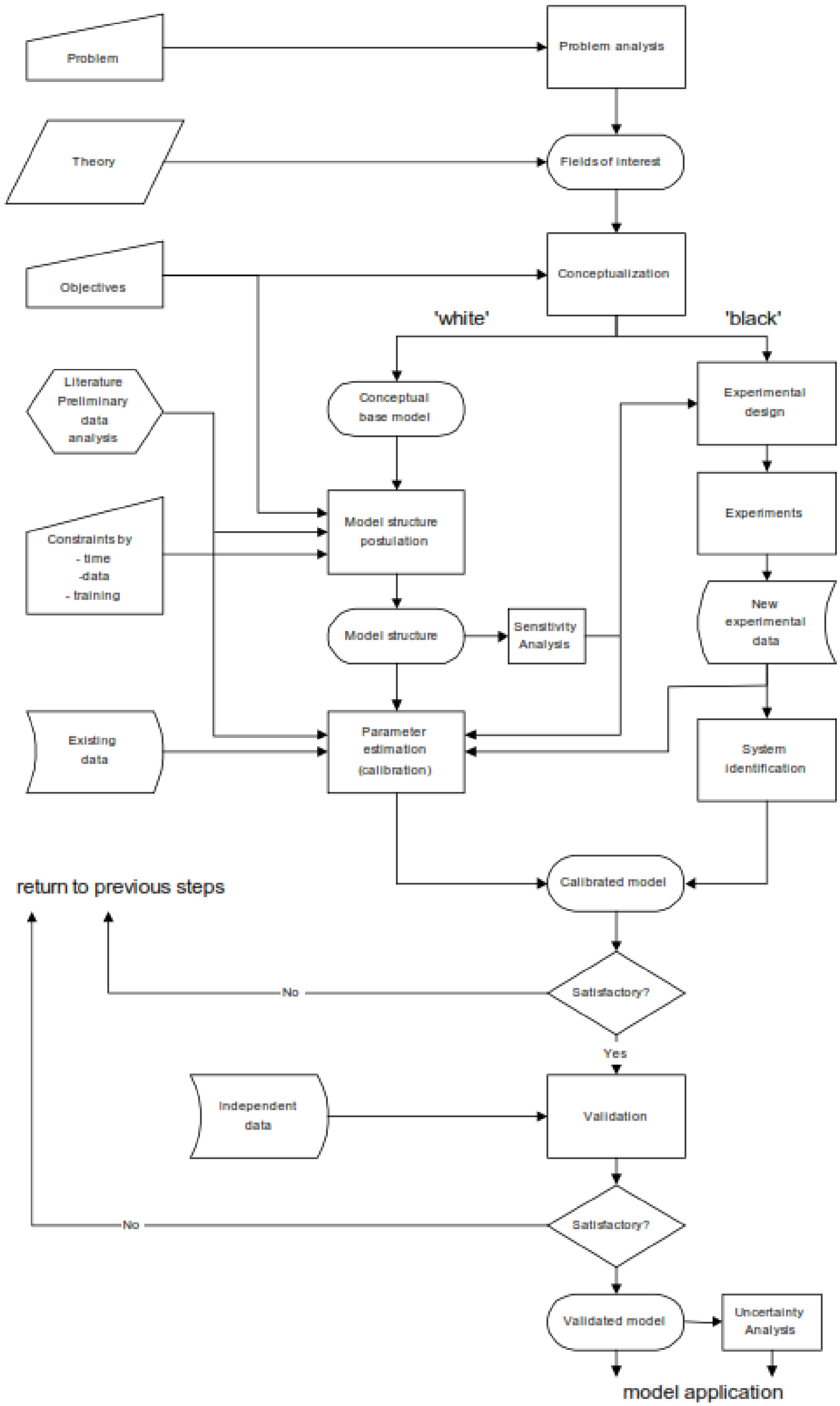

Figure 1. Scheme of the modelling procedure (van Straten, 2011)

1.1 General objective

- To develop, analyze and evaluate a dynamic model of growth, transpiration and nitrogen uptake for tomato crop (*Solanum Lycopersicom* L.) in greenhouse for soilless culture.

1.2 Particular objectives

1. To propose the mathematical structure of a new model (HORTSYT) for photo-thermal time (PTI), dry matter production (DMP), leaf area index (LAI), nitrogen uptake (Nup) and Transpiration (ETc) of a greenhouse crop.
2. To evaluate and quantify the uncertainty and a global sensitivity analysis of the HORTSYST model.
3. To carry out the calibration of the parameter's HORTSYST model.
4. To give a proposal of the application of the HORTSYST model for Irrigation scheduling and nitrogen supply.

1.3 Organization of the content of the thesis

The research report is divided into 6 chapters, each with different content and conclusions.

In **chapter 2** is described the mathematical structure of the HortSyst model developed for tomato for Mexican greenhouses and compares the performance of this model versus VegSyst model developed for Spain greenhouses in order to have an overview of the effectiveness to predict variables that describes the yield of crop tomato. **In chapter 3**, the HortSyst model was calibrated with a local optimization method and the quality of predictions is showed with the correct parameter values for autumn-winter season. **In chapter 4** an uncertainty analysis was carried of the model using two method one was a frequentist method (Monte Carlo) and another one was the Generalized Likelihood Uncertainty Estimation (GLUE) a Bayesian approach. **Chapter 5** contains an uncertainty analysis with frequentist method, for the first version of modifying of VegSyst model before establishing the final mathematical structure of HortSyst model. **Chapter 6** in this chapter are presented the global sensitivity analysis and is described the calibration of the model using a genetic algorithm to find the correct values of the more influent parameters of the HortSyst model. **Chapter 7** describes the proposal made to the model for using in the irrigation programming and schedule of Nitrogen supply. And finally the chapter 8 have the general conclusions of this thesis.

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2. COMPARISON OF THE PERFORMANCE OF THE VEGSYST AND HORTSYST MODEL: TWO CROP MODELS TO PREDICT GROWTH, NITROGEN UPTAKE AND EVAPOTRANSPIRATION OF GREENHOUSE TOMATOES

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Abstract

HortSyst model is a new discrete time model for describing the dynamics of photo-thermal time (PTT), dry mater production (DMP), N uptake (Nup), leaf area index (LAI) and transpiration rate (ETc) of greenhouse crops. The first three variables are considered as state variables and the last two are conceptualized as output variables. This model was developed to be used as a tool for decision support systems in Mexican greenhouses. The model assumes that crops have no water and nutrient limitations. The model input variables are hourly measurements of air temperature, relative humidity, and the integration of the solar radiation. HortSyst has a total of thirteen parameters. In order to test model predictions two experiments were carried out under greenhouse conditions, during the autumn-winter, and spring-summer season, in Chapingo, Mexico. Tomato (*Solanum lycopersicom L.*) crop cultivar "CID F1" were grown in hydroponic systems. Plants were distributed with a density of 3.5 plants m^{-2}. For the first experiment tomato were transplanted on 21 August 2015 and the second experiment were transplanted on 24 April 2016. A weather station was installed inside of the greenhouses, temperature and relative humidity were measured with an S-TMB-M006 model sensor, global radiation was measured with a S-LIB-M003 sensor. In each experiment, three plants were chosen randomly and harvested every ten days to measure DMP, LAI, and Nup

accumulation. The crop transpiration rate (ETc) was measured every minute by means of a weighing lysimeter, equipped with a tray carrying four plants for both experiments. The HortSyst proposed model described in this paper can be used as a decision-support tool in greenhouse production systems, since according to the fitting of its predictions against the measurements it can be helpful in water and N supply.

Keywords: water consumption, extraction curve, decision-support system, potential growth model

2.1 Introduction

Plant growth modelling has become a key research activity, particularly in the fields of agriculture, forestry and environmental sciences. Due to the growth of computer power and resources and the sharing of experiences between biologists, mathematicians and computer scientists, the development of plant growth models has progressed enormously during the last two decades. The use of an interdisciplinary approach is necessary to advance research in plant growth modelling and simulation (Thornley and France, 2007; Fourcaud et al., 2008). The efficient management of intensive agriculture demands consideration of the factors that determine the crop production potential and their interactions. The integration of these factors under the systems approach and based on growth simulation models is an approximation that allows the design of practices of management aimed at increasing productivity by minimizing the environmental impact caused by agricultural activity (Stockle et al., 1994).To increase knowledge of cropping systems and to look for practical applications, several models have been developed for greenhouse crops. Specifically for tomatoes have been proposed TOMGRO (Jones et al., 1991), TOMSIM (Heuvelink et al., 1999), TOMPOUSSE (Abreu et al., 2000) models, which have helped to simulate the behavior of production systems. However, some of these models are too complex because they involve too many state variables, input variables or model parameters, which make their implementation difficult. For example the model TOMGRO ver. 1.0 has 69 state variables, TOMGRO ver. 3.0

has 574 state variables, or the simplified version of this same model that presents 5 state variables and 29 parameters (Vazquez et al., 2014). Other models for greenhouse crops, although simpler, have been developed for crop systems specific to a region such as the VegSyst model (Gallardo et al., 2011; Gimenez et al., 2013; Gallardo et al., 2014; Gallardo et al., 2016). In order to have an optimal control in the management of productive systems, it is necessary to develop models with the capacity to represent the interactions that exist between the development of the crop, climatic conditions and physiological processes of water and nutrients uptake. Thus, to find the concentration of the optimal nutrient solution, is the most desirable in a production system, this fact considers an important effect of the transpiration and irrigation management on the nutritional absorption since the dissolved ions in the nutrient solution are transported from the root through mass flow, in which transpiration is the process that provides the necessary force for the movement to occur (Mengel et al., 2001). Therefore, with the use of a mathematical model, the perfect synchronization between the amounts of water required for growth and the nutritional demand of the crop depending from the environmental conditions, allows efficient use of water in the greenhouse crops.

Nowadays, some of the scheduling of irrigation of hydroponic culture mode used in greenhouses is based either on time clock or by radiation method, but some of these are not flexible enough to satisfy the varying crop water requirements through the day and during de season, in case of time clock, and another as, the radiation method does not take into account the influence of vapor pressure deficit so this method is an approach of the reality, but not the complete solution according to (Lizarraga et al., 2003).

The HortSyst model is a new discrete time dynamic model that predicts: photo-thermal time, dry matter production, N uptake, leaf area index and crop transpiration rates. The development of this model started by modifying the structure of the VegSyst model (Gallardo et al., 2011; Gimenez et al., 2013; Gallardo et al., 2016) proposed for greenhouse crops. However, these modifications became increasingly large and ended up being a new model considerably simpler and with predictive quality equal or greater than the VegSyst model. The objective of this work is to describe the mathematical model HortSyst that was developed as a tool capable of being used by producers in the decision making on the nitrogen supply from the simulation of biomass production and irrigation programming using the transpiration in a crop of hydroponic tomato (*Solanum lycopersicom* L.) in greenhouse

2.2 Materials and methods

2.2.1 HortSyst Model Description

The HortSyst model is a nonlinear dynamic growth model for hydroponic systems, for tomato (*Solanum lycopersicom* L.) in greenhouses. This model was developed to be used as a tool for decision support systems in Mexican greenhouses. The model assumes that crops have no water and nutrient limitations, also that the crop is free of pests and diseases, and under management in cultural activities similar to commercial greenhouses.

The HortSyst model predicts crop biomass production ($DMP, g\ m^{-2}$), N uptake ($Nup, g\ m^{-2}$), photo-thermal time ($PTI, MJ\ d^{-1}$) as state variables and the crop transpiration rates (ETc, kgm^{-2}) and leaf area index ($LAI\ , m^{2}m^{-2}$) as output variables. The model inputs variables are hourly measurements of air temperature (°C), relative humidity (%), and the integration of solar radiation (Wm^{-2}). It has thirteen parameters (Table 1) besides initial conditions of dry matter production and photo-thermal time. The HortSyst model was developed based on the VegSyst model (Gallardo et al., 2011; Gallardo et al., 2016; Gallardo et al., 2014; Giménez et al., 2013; Granados et al., 2013; Gallardo et a., 2016). The following Forrester diagram (Figure 2.1) summarizes the functional relationship that exists between the components of the model as input, output, parameters and state variables.

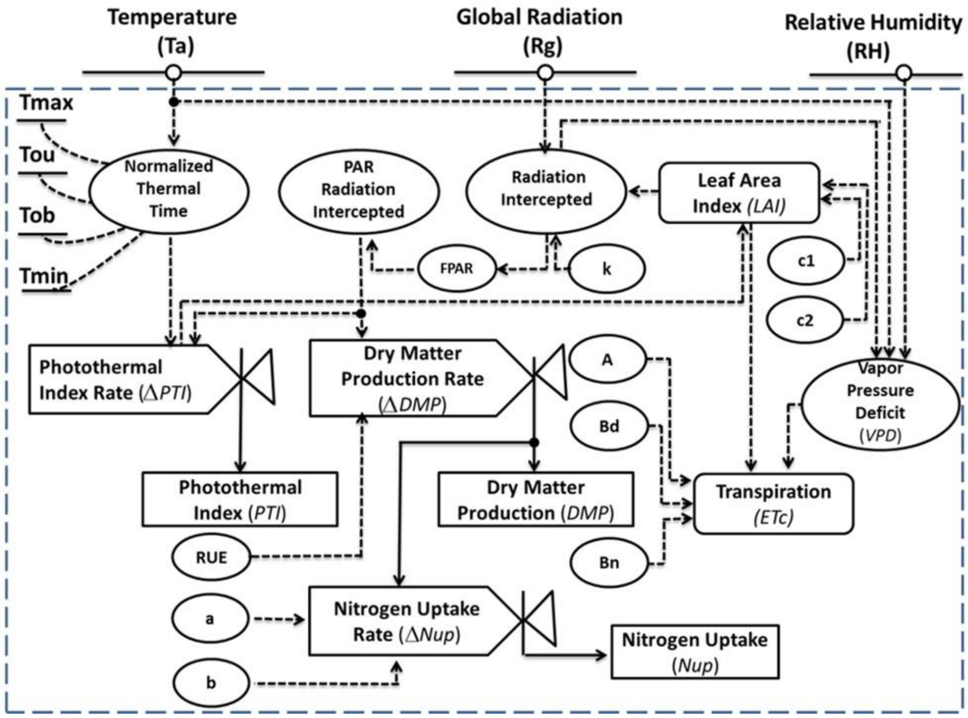

Figure 2.1. Forrester diagram for HortSyst model

The HortSyst model predicts in discrete time, namely, by means of difference equations the behavior of the three state variables; the photo-thermal time (eq.1), the dry matter production (eq.2) and the nitrogen uptake (eq.3).

$$PTI(j+1) = PTI(j) + \Delta PTI \tag{1}$$

$$DMP(j+1) = DMP(j) + \Delta DMP \tag{2}$$

$$N_{up}(j+1) = N_{up}(j) + \Delta N_{up} \tag{3}$$

where the values of each variable in discrete time $j + 1$ are calculated by adding the values of the variables in the previous discrete time j plus the rate of change Δ corresponding to each variable.The variable photo-thermal time ($PTI, MJ\ d^{-1}$) is defined as the state variable since it couples the effect of radiation and temperature on the crop and from the point of view of the climate of the greenhouse, these variables are not strongly correlated as they are in the open field (Reffye et al., 2009; Dai et al., 2006; Xu et al., 2010). In contrast to other researchers who have modeled the leaf area index as a function of time or as a function of the day degrees (Carmassi et al., 2013; Chin et al, 2011; Incrocci et al., 2008; Massa et al., 2011; Medrano., 2008; Montero ., 2001; Orgaz et al., 2005) or others who have used the days after transplant (Carmassi et al., 2007; Medrano., 2005; Medrano et al., 2011; Ta et al., 2011) or the specific leaf área (Bechini et al, 2006; Stockle et al, 2003), in the HortSyst model, the photo-thermal time state variable as the independent variable of the leaf area of the crop. In the VegSyst model, the thermal time is the state variable that drives the daily calculation of biomass production, nitrogen uptake and crop evapotranspiration (Gallardo et al., 2011; Gimenez et al., 2013). In addition, radiation directly influences crop growth (dry matter production) and affects development (morphogenesis) (Sergio et al., 2003).

The rate of change of the photo-thermal time (ΔPTI) depends on the photosynthetically active radiation(PAR), normalized thermal time (TT) and the intercepted fraction of radiation$(f_{i-PAR)}$.

$$\Delta PTI(j) = \left(\sum_{i=1}^{24} TT(i,j)\right) / 24 \times PAR(j) \times f_{i-PAR}(j) \qquad (4)$$

where the index i represents hourly calculations, index j represents daily level, PAR is photosynthetically active radiation and is calculated from daily global radiation above the crop (R_g,$W\ m^{-2}$).

$$PAR = 0.5 \times R_g \qquad (5)$$

TT °C is the normalized thermal time as used by other researchers (Bechini et al., 2006; Soltani et al., 2012;), which is defined as the ratio of the rate of growth under real conditions of optimal temperatures, and is calculated as follows:

$$T = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases} \qquad (6)$$

where T_a (°C) is the temperature of the air, $T_{\min}$ (°C) is the minimum temperature, $T_{\max}$ (°C) is the maximum temperature, T_{ob} (°C) is the lower optimal temperature and T_{ou} (°C) is the upper optimal temperature.

The intercepted fraction of the radiation is calculated by the exponential function:

$$f_{i-PAR} = 1 - \exp(-k \times LAI(j)) \tag{7}$$

where k is the light extinction coefficient, and LAI is the leaf area index which in turn is calculated from the leaf area value A_f (m^2) which depends on the daily photo-thermal time (ΔTPI) by an equation type Michaellis-Menten.

$$LAI(j) = \left(\frac{c_1 PTI(j)}{c_2 + PTI(j)} \right) d \tag{8}$$

where c_1 (m^{-2}) and c_2 are parameters of the Michaellis-Menten equation and d ($\mathrm{plants\,m}^{-2}$) is the density of the crop.

The model uses a classical concept approach, efficient radiation applications (Kang et al., 2008; Lemaire et al., 2008; Reffye et al., 2009) which allows the calculation of daily dry matter production (ΔDMP) as a function of the photosynthetically active radiation (PAR) eq. (5), crop characteristics such as leaf area index (LAI) eq. (8) and the radiation use efficiency parameter (RUE, gMJ^{-1}) as has proposed by several researchers (Gallardo et al., 2016; Shibu et al., 2010; Soltani and Sinclair, 2012).

$$\Delta DMP(j) = RUE \times f_{i-PAR} \times PAR(j) \tag{9}$$

The value of (ΔDMP) accumulates day by day as in equation (2)

Once the daily dry matter production is calculated, it is possible to calculate the nitrogen uptake daily by the equation(10, 11) (Le Bot et al., 1998; Tei et al., 2002) which, when accumulated with equation (3), allows the calculation of the nitrogen extraction throughout the crop growing period (ΔDMP).

$$\%N(j) = a \times (DMP(j))^{-b} \tag{10}$$

$$N_{up}(j) = (\%N(j)/100) \times DMP(j) \tag{11}$$

where ΔN_{up} is the daily uptake nitrogen ($g\,m^{-2}$), a and b are parameters of the equation and ΔDMP is the increase of daily dry matter produced ($g\,m^{-2}$).

Finally, crop transpiration $(ETc, kg\,m^{-2})$ is calculated every hour using the equation proposed by Baille et al. (1994), which has been widely used to schedule greenhouse irrigation (Carmassi et al., 2013; Martínez-Ruiz et al., 2012; Massa et al., 2011; Medrano et al., 2011). The Baille transpiration model requires the global radiation data, vapor pressure deficit, which is calculated with values of air temperature and relative humidity and leaf area index equation (8). The equations that in HortSyst estimate the transpiration of the crop are:

$$ETc(i) = A \times (1 - \exp(-k \times LAI(j))) \times Rg(i) + LAI(j)VPD(i)B_{(d,n)} \tag{12}$$

$$ETc(j+1) = \sum_{i=1}^{24} ETc(i) \tag{13}$$

where $ETc(j+1)$ ($kg\,m^{-2}d^{-1}$) is the daily accumulated transpiration, $ETc(i)$ ($g\,m^{-2}h^{-1}$) is the hourly transpiration rate, R_g is the hourly incident solar radiation ($W\,m^{-2}$), VPD is the vapor pressure deficit and A (dimensionless) refers to the radiative parameter; and B_d, B_n (Wm^2kPa^{-1}) are parameters of the aerodynamic term of equation (13) for day and night, respectively.

2.2.2 The computational model

The HortSyst is currently programmed in the Matlab computer environment. The dynamic equations are coded inside a Matlab subroutine (function). Two iterative loops allow computing daily and hourly calculations. The outputs of the subroutine are the variables; photo-thermal time, crop biomass, nitrogen uptake, crop evapotranspiration and leaf area index. The input variables of the subroutine are the model parameters (Table 1) and climatic variables. A main program (Matlab script) calls the subroutine and generating graphs or other calculations necessary to run the simulations.

2.2.3 Tomato growth experiments description

Two experiments were carried out under greenhouse conditions, during the autumn-winter, and spring-summer season, located at the University of Chapingo, Mexico. Geographical location: 19° 29' NL, 98° 53' and 2240 msnm. A tomato (*Solanum lycopersicom* L.) crop cultivar "CID F1" was grown in a hydroponic system using volcanic sand as substrate and fertilized with Steiner nutrient solution (Steiner, 1980). Plants were distributed with a density of 3.5 plants m^{-2}. For the first experiment tomato seeds were sown on 18 July 2015 and the plants were transplanted on 21 August 2015 in a glass greenhouse type chapel with 8 x 8 m dimension, and the second experiment were sown on 24 March 2016 and transplanted on 24 April 2016 in a plastic greenhouse with overhead ventilation with dimension of 8 x 15 m. A weather station (Onset Computer Corporation) was installed inside of the greenhouses. Temperature and relative humidity were measured with a S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with a S-LIB-M003 sensor and was located 3.5 m above the ground. Both sensors were connected to a datalogger U-30-NRC model, which recorded data every minute.

In each experiment, three plants were chosen randomly for the sample each 10 days to measure dry matter, nitrogen uptake accumulation and leaf area index. Plants were dried out during 72 h at 70 °C. And nitrogen was determined by Micro-Kjeldahl method (Chapman and Pratt, 1974). Leaf area Index were determinate by a nondestructive method, it consisted in taking 4 plants randomly in order to get measurements of width and length of the plants leaves and also the total leaf area and a plant canopy analyzer LAI-3100 (LICOR, USA) was used. From the measurements, nonlinear regressions models were fitted in order to estimate this variable. The crop transpiration rate was measured every minute by means of a weighing lysimeter located in a central row of the greenhouses, the device include an electronic balance (scale capacity =120 kg, resolution ± 5 g equipped with a tray carrying 4 plants for both experiments. The weight loss measured by the electronic balance was assumed equal to the crop transpiration.

In order to compare the predictive quality of the HortSyst and VegSyst models we used the nominal parameters listed in Table 2.1 for the HortSyst model and the parameters used for the simulation VegSyst model were taken from Gallardo et al.(2014); Gallardo et al.(2016). And MAE and RMSE statistics were considered to evaluate the performance of simulation of both models.

Table 2.1. Model parameters used for HortSyst model during greenhouse growing condition.

No	Parameter	Symbol	Units	Nominal Value (autumn-winter)	Nominal Value (spring-summer)	source
1	Top upper temperature	T_{max}	°C	35.00	35.00	Peet and Welles (2005), Chu et al., (2009)
2	Top bottom temperature	T_{min}	°C	10.00	10.00	Peet and Welles (2005), Chu et al., (2009)
3	Optimum minimum temperature	T_{ob}	°C	17.00	17.00	Peet and Welles (2005)
4	Optimum maximum temperature	T_{ou}	°C	24.00	24.00	Peet and Welles (2005)
5	Radiation Use Efficiency	RUE	g MJ^{-1}	4.01	3.1	Gallardo et al., (2014), Challa and Bakker (1998)
6	Extinction coefficient	k	---	0.70	0.70	
7	N concentration in the dry biomass at the end of the exponential growth period	a	g m^{-2}	7.55	7.55	Gallardo et al., (2014)
8	Is the slope of the relationship	b	---	-0.15	-0.15	Gallardo et al., (2014)
9	Slope of the curve	c_1	m^{-2}	2.82	3.07	Estimated
10	Intersection coefficient	c_2	---	74.66	175.64	Estimated
11	Radiative coefficient	A	---	0.59	0.24	Montero et al., (2001), (Medrano et al., (2008)
12	Aerodynamic coefficient during day	B_d	W m^{-2} kPa^{-1}	19.10	37.6	Montero et al., (2001),Medrano et al., (2008)

13	Aerodynamic coefficient during night	B_n	W m-2 kPa-1	25.00	26	Montero et al.,(2001), Medrano et al.,(2008)

2.3 Results

2.3.1 Simulation of HortSyst Model

2.3.1.1 Input variable

The global solar radiation (Rg), air temperature (Ta), and relative humidity (RH) used in the simulations of the HortSyst and VegSyst model for both growing periods autumn- Winter (O-W) and spring summer (S-S) crop cycle are showed in Figure 2.2, 2.3 and 2.4, respectively. The nominal values of the model parameters are given in Table 2.1.

According to measured data it is clear that the amount of global radiation in the spring summer season is a more than twice the one is reached in the autumn-winter season. Furthermore, during autumn-winter we observed greater cloudy days. This fact has its effect on the accumulation of dry matter, nitrogen uptake, leaf area index and water uptake (transpiration).

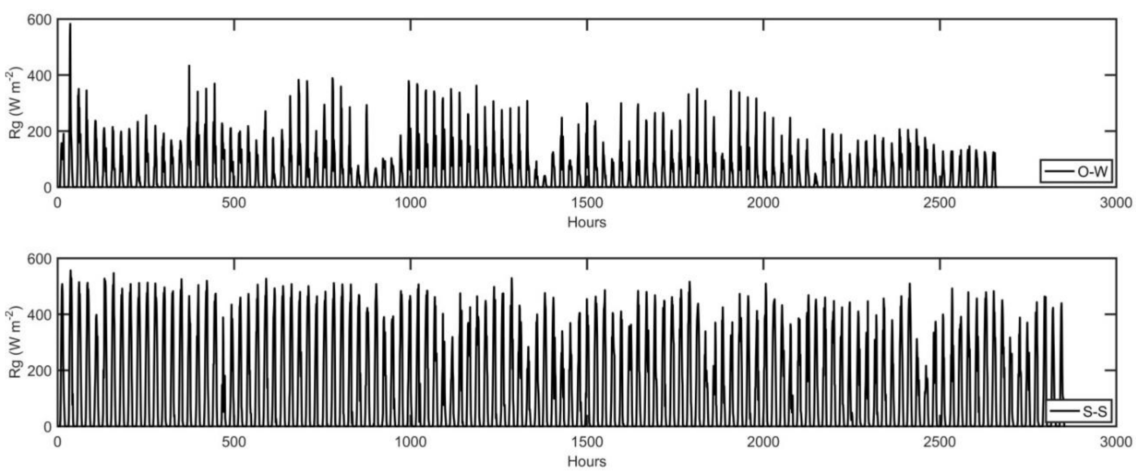

Figure 2.2. Global radiation measured hourly inside of the greenhouse located in Chapingo, Mexico during autumn-winter (O-W), 2015, and Spring-Summer (S-S), 2016.

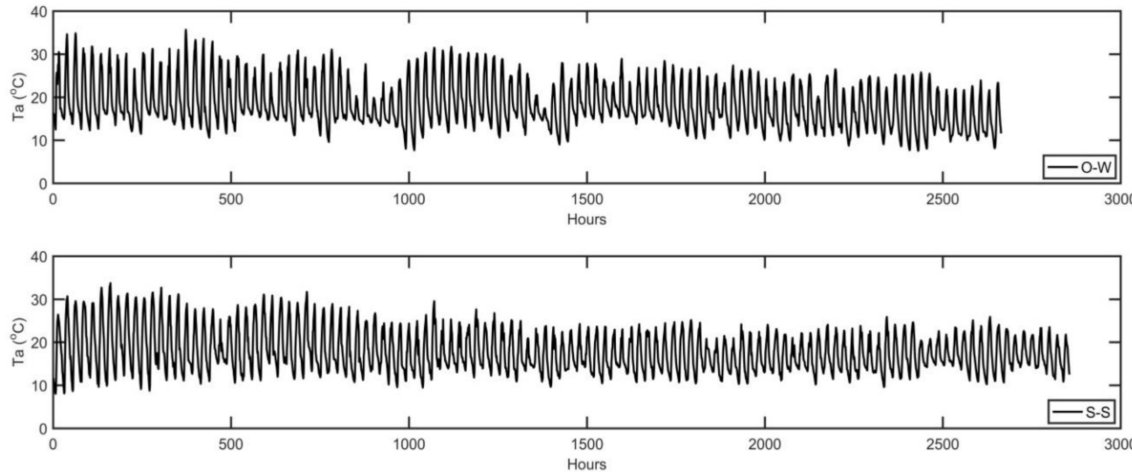

Figure 2.3. Air temperature measured hourly inside of the greenhouse, located in Chapingo, Mexico, during autumn-winter (O-W), 2015 and Spring-Summer (S-S), 2016

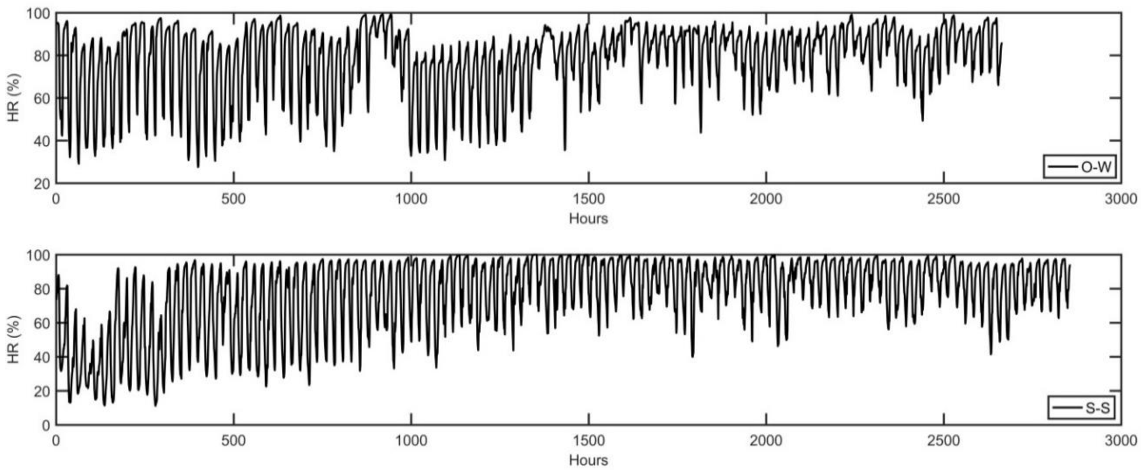

Figure 2.4. Relative Humidity measured hourly inside of the greenhouse located in Chapingo, Mexico, during autumn-winter (O-W), 2015 and Spring-Summer (S-S), 2016

2.3.1.2 Dry matter Production (DMP)

Figure 2.5 shows the values of the simulation for dry matter production using RUE values of 4.01 g MJ^{-1} for the autumn-winter and RUE of 3.01 g MJ^{-1} for the spring summer, where it is observed that during the spring summer season for both HortSyst and VegSyst models, there was approximately twice the biomass with respect to the autumn-winter, this is due to the fact that it is the cycle in which there is more solar radiation (Figure 2.2).

It was found that the simulation follows the trend of the measured values in laboratory having as accumulated final value of simulated biomass in the autumn-winter cycle of 587.37 g m^{-2} against a measured value of 673.38 g m^{-2} which represents an underestimation of the model of 12.77% of the measured value. In case of the spring-summer period, the simulated value at the end of the cycle is 1336.59 g m^{-2} against the measured 1304.118 g m^{-2}, resulting in an overestimation error of 2.49%. This means that the RUE value considered could be used for the simulation of the biomass.

In both experiments total dry matter production shows an exponential growth and then an approximately linear growth phase, which is a growth pattern, expected under constant climate conditions.

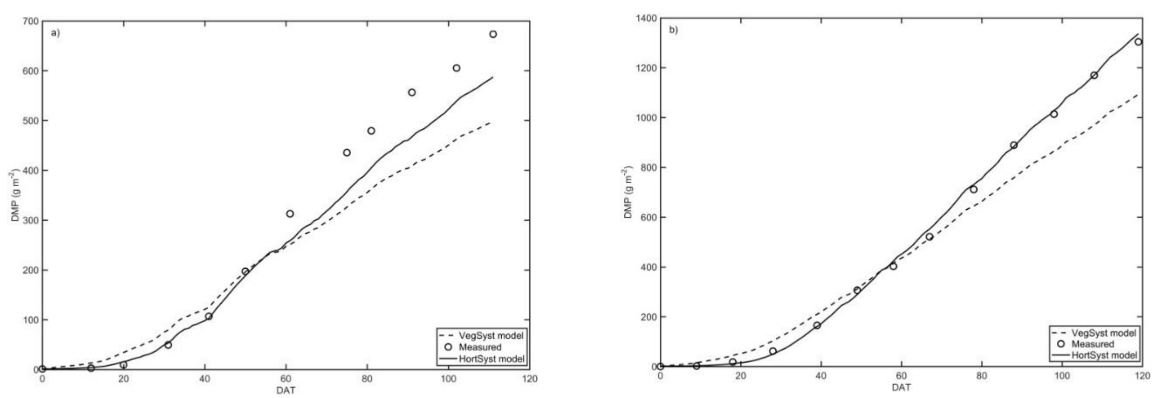

Figure 2.5. Time course of the simulated and measured values of dry matter production of a greenhouse tomato crop grown in Chapingo, Mexico, for a) autumn-winter, 2015 and b) spring-summer, 2016 for HortSyst and VegSyst models

2.3.1.3 Nitrogen Uptake (Nup)

On the other hand, Figure 2.6 shows a comparison between the values measured and predicted by the HortSyst model and VegSyst model, for the nitrogen uptake variable for both crop seasons. In both cases a good fit between simulations and measurements is observed for the case of nitrogen uptake in autumn-winter, the final value predicted by the simulation is 19.98 g m^{-2} against the measured value of 13.71 g m^{-2} which represents an error of 45.78%. In case of Spring-Summer the value simulated was 40.23 g m^{-2} and the measured was

27.4 g m^{-2}. In both periods error of predicted value by the model is approximately of 46% above measurements (Figure 6).

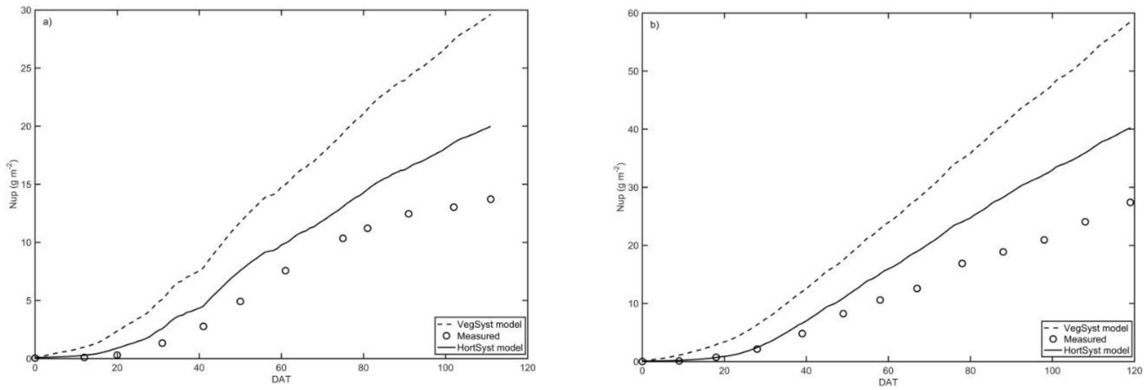

Figure 2.6. Time course of the simulated and measured values of Nitrogen uptake of a greenhouse tomato crop grown in Chapingo, Mexico, for a) autumn-winter, 2015 and b) Spring-Summer, 2016, for HortSyst and VegSyst models

2.3.1.4 Leaf Area Index (LAI)

Because the lack of information in the literature of the parameters values of this variable (c_1 and c_2) a manual calibration was carried out in order to determine the possible values could be used in the simulation for each growing period. It is possible that, this variable plays central role in the model since, from these simulated values is predicted photo-thermal time, dry matter production, transpiration and indirectly nitrogen uptake. The considered values for the parameters are showed in Table 2.1. Their values are longer for spring-summer than for autumn-winter.

The simulated LAI values are similar to the measured values 5.85 m^2m^{-2} with an error of 0.4% between the measured and simulated data (5.83 m^2m^{-2}), during autumn-winter and during spring-summer, the measured LAI was 7 m^2m^{-2}, against 6.86 m^2m^{-2} with an error of 2.17% for the measured and simulated data as shown in the figure 2.7. LAI is only simulated by the HortSyst model. The VegSyst model does not take in account the computation of LAI, because it uses another concept like heat units and intercepted PAR radiation for two stages of the crop.

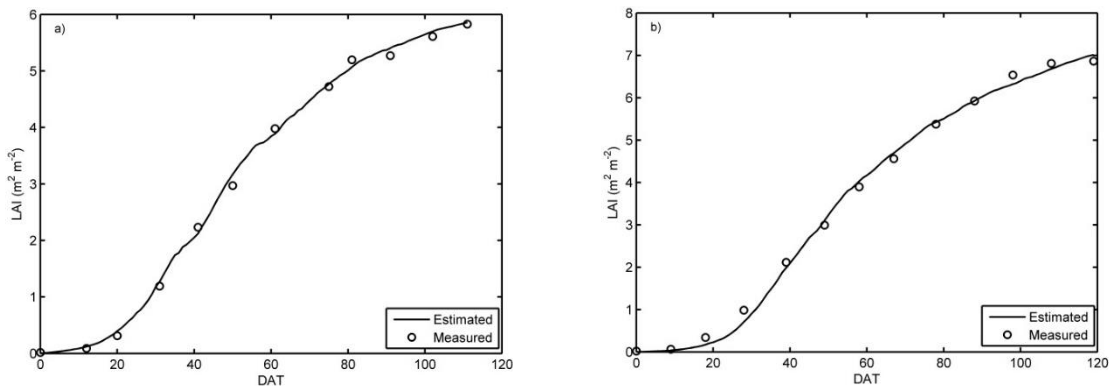

Figure 2.7 Time course of the simulated and measured values of the Leaf Area Index of a greenhouse tomato crop grown in Chapingo, Mexico for, a) Autumn-Winter, 2015 and b) Spring-Summer, 2016, for HortSyst model

2.3.1.5 Crop transpiration rate (ETc)

For the transpiration variable (Figure 2.8), it was found that using the parameters values shown in Table 1 for A, Bd and Bn, it is acceptable to estimate with an error of 2.62%, for an accumulated simulated value of 183.68 kg m^{-2} and measured values and 188.49 kg m^{-2} at the end of the cycle autumn-winter and measured value of 291.69 kg m^{-2} against simulated of 294.2 kg m^{-2} with error of 0.88% for spring and summer, respectively.

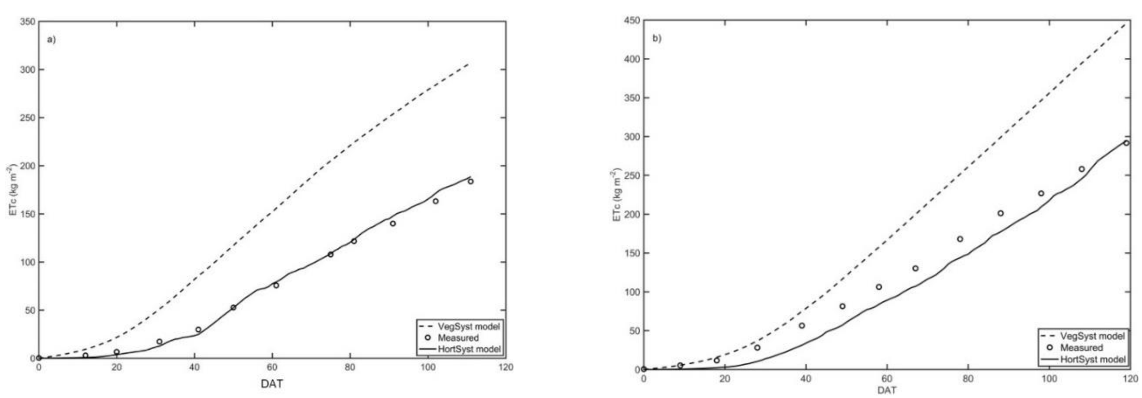

Figure 2.8.Time course of the simulated and measured values of crop transpiration of a greenhouse tomato crop grown in Chapingo, Mexico a) Autumn-Winter, 2015 and b) Spring-Summer, 2016, for HortSyst and VegSyst models

2.3.1.6 Photo-thermal time (PTI)

Figure 2.9 shows the photo-thermal time variable that uses this model to calculate the leaf area index which presents a behavior similar to that previously reported by Xu et al., (2010). It is important to emphasize that this simulation is intended to demonstrate the ability of the model to predict the most important variables related to the production of a hydroponic tomato crop under greenhouse conditions and using volcanic sand ("tezontle") as substrate. Using the temperature at 1.5 m above ground and PAR above canopy this photo-thermal model eq. (4) gave satisfactory prediction of leaf area index eq.(8)

The amount of photo-thermal time accumulated in autumn winter was 108.97$MJ\ d^{-1}$ and for spring summer of 327.56 $MJ\ d^{-1}$ representing a 3 times greater difference in spring- summer. Like LAI variable the HortSyst model simulates PTI during the crop cycle this is the main difference between HortSyst and VegSyst model.

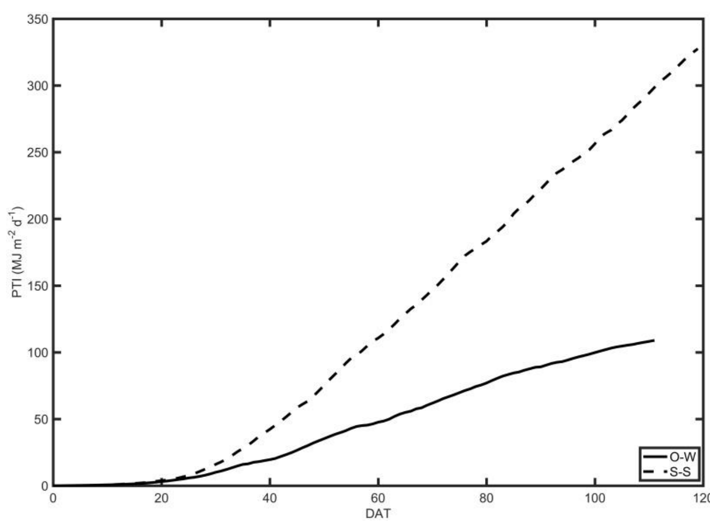

Figure 2.9.Time course of the predicted of photo-thermal time by HortSyst model, accumulated since plant date for Autumn-Winter (O-W) and Spring-Summer (S-S)

From the simulations carried out for the HortSyst and VegSyst model, the HortSyst model provides better predictive quality for dry matter production, nitrogen uptake and transpiration than the VegSyst model, this is confirmed by the higher values of the statistics; MAE and RMSE (Table 2) for this last model for both crop season, spring-summer and autumn-winter, with the highest errors for the case of transpiration in the VegSyst model. The variable leaf area index was not compared since both models do not share the simulation of this variable in its mathematical structure.

Table 2.2. Summary of results of the statistical indices (MAE and RMSE) used to evaluate the performance of the HortSyst model and VegSyst model for simulation of DMP, Nup, ETc and LAI during Autumn-Winter, 2015 and Spring-Summer, 2016

	HortSyst Model		**VegSyst Model**	
		Autumn-Winter		
OUTPUT	MAE	RMSE	MAE	RMSE
DMP	39.35	53.60	69.70	93.04
Nup	2.56	3.19	7.29	8.82
ETc	3.51	4.37	67.77	80.49
LAI	0.09	0.10		
		Spring-Summer		
DMP	12.93	16.71	70.14	101.17
Nup	5.25	7.03	13.54	16.99
ETc	15.94	18.16	59.96	79.53
LAI	0.12	0.14		

In order to show a potential use of the HortSyst model to predict the concentration of nitrogen uptake by the crop as a function of the transpiration, in figure 2.10 shows daily N absorbed concentration, considering the amount of water absorbed daily by the process of transpiration predicted by the model, for the spring-summer and autumn-winter crop cycles.

Where in the first 35 days, the uptake concentration by crop exceeds the concentration of 12 me L^{-1} (168 mgL^{-1}) recommended by Steiner (1980), after 40 days of cultivation, the concentration decreases approximately half of the concentration applied to the crop. With the evaluation of performance of the model, it was found that it would be a waste of approximately 50% of the applied fertilizer considering an efficiency of 100% of the system production under soilless culture.

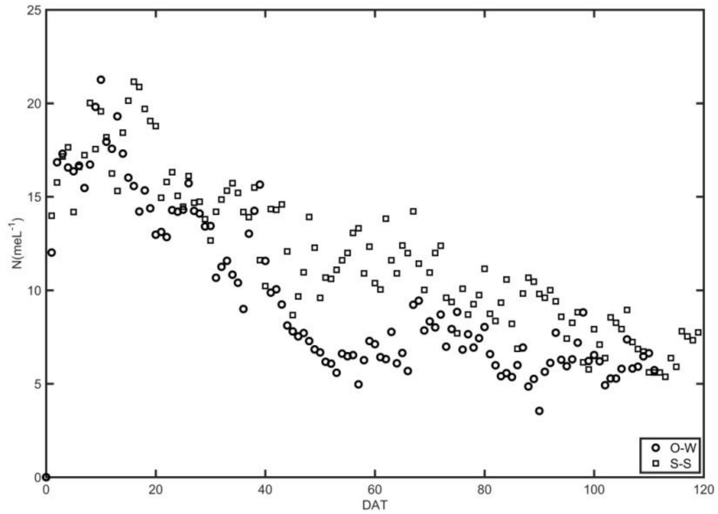

Figure 2.10.Time course of simulation of daily value of N concentration (meL-1) nitrogen uptake during Autumn-Winter (O-W), 2015 and Spring-Summer (S-S), 2016

2.4 Discussion

The crop simulation models HortSyst and VegSyst were simulated to show its performance for tomato for Mexican greenhouses. HortSyst model predicts correctly crop biomass, photo-thermal time and predicts accurately leaf area index and transpiration crop, however the quality of prediction of N uptake is poor using the nominal parameter values. This means that to improve the predictive quality of the model not only for N uptake but also for the other variables parameter estimation of model calibration is required by using experimental data.

The quality of the simulated values of dry matter production are acceptable, because of the results obtained in the simulation using the RUE value of 4.01 g MJ^{-1} for prediction of biomass reported by (Gallardo et al., 2016) and RUE 3.01 g MJ^{-1} reported by (Challa and Bakker,1998), for tomato crop, biomass values at the end of cycle are slightly lower than those reported by Gallardo et al., (2014) for autumn-winter. The value of this parameters are different due to differences in climatic conditions between one region and another or to different crop cycles (Cota et al.,2014.).

The measured N uptake values were quite similar to those results reported for tomato crop by Gallardo et al., (2016); Gallardo et al. (2014). The differences in the values accumulated for nitrogen uptake between both cycles at the end of these are because in each cycle the environmental conditions are not the same at least in the levels of radiation and maybe the temperature variation between the day and night. The parameters used in the model for these variables were the same for the two crop cycles reported by Gallardo et al. (2016); Gallardo et al. (2014) since no values were found for each different cultivation period, in both cases the model did not show a satisfactory fit because the authors calibrated the model for nitrogen in a different culture system. The modeling of LAI is one of the important differences with respect to the VegSyst model proposed by (Gallardo et al., 2011, 2016, 2014; Giménez et al., 2013; Granados et al., 2013), since these authors did not include the simulation of this variable in their model.

The final accumulated measured of evapotranspiration value for the autumn-winter is similar to those reported by (Gallardo et al., 2016; Gallardo et al., 2014). It is important to mention that the methodology to model water consumption by these authors was different since they used the Penman-Monteith model with crop coefficients. The values of the parameters in the HortSyst model are slightly similar to those reported by (Martínez-Ruiz et al., 2012;) since these authors performed the calibration using frequent climatic data of 15 minutes and hourly.

In case of photo-thermal time Xu et al.(2010) found that modeling the leaf area index using this concept gave better predictions than degrees days model as (Gallardo et al., 2016) the latter type of models overestimate the predictions because of the fact that inside of the greenhouse the global radiation is not synchronized with the temperature behavior (Reffye et al., 2003; Xu et al., 2010). On the other hand, when comparing the estimation of leaf area index using the specific leaf area as used in Stockle et al. (1994) presents a poorest predictions due to the large variation of the specific leaf area among different growing seasons and the data of this latter variable can only be obtained by destructive measurements, this limits the application of models based on specific leaf area to greenhouse crops and climate management practice (Xu et al., 2010).

The advantage of using a model to make fertilization recommendations is that it considers factors as; environment conditions, physiological processes such as transpiration and characteristics of the crop as leaf area index and biomass production. The results found that with the model without calibration the simulation are quite similar to those reported (Gallardo et al., 2014) for the Autumn-winter season, who evaluated the use of the model VegSyst under three scenarios of recommendation of fertilization.

2.5 Conclusions

The HortSyst model can be used as a decision-making tool in greenhouse production systems, since according to the presented simulation it predicts in an acceptable way the biomass, absorbed nitrogen, leaf area index and transpiration. In order to model the leaf area index, a new concept called the photo-thermal time, which represents the effect of temperature on leaf expansion and the effect of radiation on crop growth, which, may be used as an alternative to simulate leaf area index in crop models. In fact there are few models that include the variable transpiration in order to be used in irrigation management, in this case, was used a model that was derived from the simplification of Penman-Monteith and for its simplicity can be used to predict the consumption of water by the crop, in addition it needs climatic variables that are commonly measured in greenhouses. It is necessary to carry out a calibration of the model to find the values of the parameters that help to improve its predictive quality. Also is necessary carrying out an evaluation (validation) of the model, with data of another experiment of the same cycle or different crop cycle to evaluate its behavior under different scenarios. Due to the small number of parameters (13 parameters) involved in the HortSyst model it is feasible to use it for irrigation management and nitrogen application in hydroponic tomato under greenhouse.

2.6 References

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3. HORTSYST: A DYNAMIC MODEL TO PREDICT GROWTH, NITROGEN UPTAKE, AND TRANSPIRATION OF GREENHOUSE TOMATOES

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Abstract

HortSyst model is a new discrete time model for describing the dynamics of photo-thermal time (PTI), total dry matter production (DMP), Nitrogen uptake (Nup), leaf area index (LAI) and, transpiration (ETc) for greenhouse crops. The first three variables are considered as state variables and the last two are conceptualized as output variables. This model was developed to be used as a tool for decision support systems in Mexican greenhouses. HortSyst has a total of thirteen parameters. In order to test model predictions, an experiment was carried out in a greenhouse during the autumn-winter season, in Chapingo, Mexico. Tomato (*Solanum lycopersicom L.*) crop cultivar "CID F1" was grown in a hydroponic system. The plants were distributed with a density of 3.5 plants m^{-2}. The tomato crop was transplanted on 21 August 2015. A weather station was installed inside of the greenhouse to measure the temperature, relative humidity and, global radiation. It was carried out a calibration of the model to estimate the correct parameter values for this crop season. The HortSyst model provides an excellent predictive quality for DMP, Nup, LAI and ETc according to the statistics; BIAS, RMSE and modellig efficiency (EF). The model proposed and described in this paper can be integrated as a decision-support tool for nitrogen supply and irrigation management in greenhouse production systems.

Keywords: water consumption, extraction curve, decision-support system, potential growth model

3.1 Introduction

Plant growth modeling has become a key research activity, particularly in the fields of agriculture, forestry, and environmental sciences. Due to the growth of computer power and resources and the sharing of experiences between biologists, mathematicians and computer scientists, the development of plant growth models has progressed enormously during the last two decades. The use of an interdisciplinary approach is necessary to advance research in plant growth modeling and simulation (Fourcaud et al., 2008). The efficient management of intensive agriculture demands consideration of the factors that determine the crop production potential and their interactions. The integration of these factors under the systems approach and based on growth simulation models is an approach that allows the design of practices of management aimed at increasing productivity by minimizing the environmental impact caused by agricultural activity. Several mathematical models have been developed to increase knowledge of cropping systems in greenhouse crops to look for practical applications. Specifically for tomatoes have been proposed TOMGRO (Jones et al., 1991), TOMSIM (Heuvelink et al., 1999), TOMPOUSSE (Abreu et al., 2000) models, which have helped to simulate the behavior of production systems. However, some of these models are too complex because they involve too many state variables, input variables or parameters, which make their implementation difficult. For example the model TOMGRO ver. 1.0 has 69 state variables, TOMGRO ver. 3.0 has 574 state variables, or the simplified version of this same model that presents 5 state variables and 29 parameters (Vazquez et al., 2014). Other models for greenhouse crops, although simpler, have been developed for crop systems specific to a region such as the VEGSYST model (Gallardo et al., 2011; Gallardo et al., 2014; Gallardo et al., 2016). It is necessary to develop models in order to have an optimal control in the management of production systems, with the capacity to represent the interactions that exist between the development of the crop, climatic conditions and physiological processes of water and nutrient uptake. The effect of the ETc and irrigation management on the nutritional absorption should be taken into account to find which concentration of the optimal nutrient solution is the most desirable in a production system since the dissolved ions in the nutrient solution are transported from the root through mass flow, in which ETc is the process that provides the necessary force for the movement of these ions (Mengel et al., 2001). The perfect synchronization between the amounts of water required for growth and the nutritional demand of the crop depend on the environmental conditions, thus, the use of a mathematical model could allow to use the water supply with high efficiency in greenhouse crops. Nowadays, some of the scheduling of irrigation of hydroponic culture used in greenhouses is based either on clock timing or by accumulated solar radiation, however these strategies are not flexible enough to satisfy the varying crop water requirements through the day and during the season. Both irrigation programming methods do not take into account the influence of vapor pressure deficit.

The HortSyst model is a new dynamic discrete time model that predicts: PTI, DMP, Nup, LAI and ETc. The development of this model started by modifying the structure of the VEGSYST model (Gallardo et al., 2011; Giménez et al., 2013; Gallardo et al., 2014; Gallardo et al., 2016) proposed for greenhouse crops. However, these modifications became increasingly large and ended up being a new model considerably simpler and with predictive quality equal or better than the VegSyst model. The objective of this work is to describe the mathematical model HortSyst that was developed as a tool capable of being used by growers in the nitrogen supply from the simulation of daily DMP and irrigation programming using the transpiration in a crop of hydroponic tomato (*Solanum lycopersicom* L.) in a greenhouse. In addition, a LAI model was included in the simulation this was estimated by the concept PTI, also a calibration of the parameters was carried out of the model.

3.2 Materials and methods

3.2.1 HortSyst Model Description

The HortSyst model is a nonlinear dynamic growth model for hydroponic systems, for tomato (*Solanum lycopersicom* L.) in greenhouses. This model was developed and adapted to be used as a tool for decision support systems in Mexican greenhouses. The model assumes that crops have no water and nutrient limitations, also that the crop is free of pests and diseases and it was cultivated under the management of the cultural activities similar to commercial greenhouses. The HortSyst model predicts crop biomass production (DMP, $g\ m^{-2}$), N uptake (Nup, $g\ m^{-2}$), photo-thermal time (PTI, $MJ\ d^{-1}$) as state variables and the crop transpiration (ETc, $kg\ m^{-2}$) and leaf area index (LAI, $m^2 m^{-2}$) as output variables. The model input variables are hourly measurements of air temperature (°C), relative humidity (%), and integration of solar radiation (Wm^{-2}) and It has thirteen parameters (Table 3.1).

The following Forrester diagram (Figure 3.1) summarizes the functional relationship that exists between the components of the model as inputs, outputs, parameters and state variables.

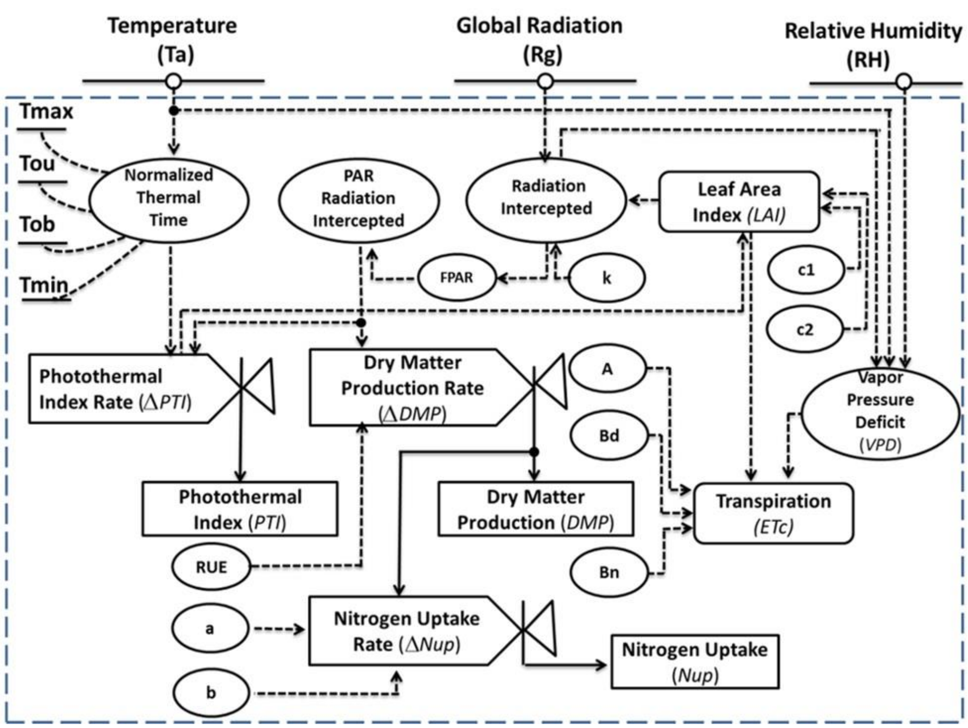

Figure 3.1. Forrester diagram for HortSyst model of a greenhouse tomato crop.

The HortSyst model predicts in discrete time, namely, by means of difference equations, the behavior of the three state variables; the photo-thermal time (equation 1), the total DMP (equation 2) and the Nup (equation 3).

$$PTI(j+1) = PTI(j) + \Delta PTI \tag{1}$$

$$DMP(j+1) = DMP(j) + \Delta DMP \tag{2}$$

$$N_{up}(j+1) = N_{up}(j) + \Delta N_{up} \tag{3}$$

Where the values of each variable in discrete time $j+1$ are calculated by adding the values of the variables in the previous discrete time j plus the rate of change Δ corresponding to each variable. The PTI is defined as the state variable that couples the effect of radiation and temperature on the crop because these variables from the point of view of the climate in the greenhouse are not strongly correlated as they are in the open field (De Reffye and Hu., 2003; Xu et al., 2010; Dai et al., 2006). In contrast to other researchers who have modeled the LAI as a function of time or as a function of the degree days (Carmassi et al., 2013; Chin et al., 2011; Massa et al., 2011; Medrano et al., 2008) or others who have used the days after transplant (Medrano et al., 2005; Ta et al., 2011) or the specific leaf area (Bechini et al, 2006), in the HortSyst model, the PTI is the independent variable in the calculation of the leaf area index of the crop. In the VEGSYST model, the thermal time is the state variable that drives the daily calculation of DMP, Nup and ETc. However, it is important to consider the radiation, because it directly influences in crop growth (DMP) and development (morphogenesis).

The rate of change of the photo-thermal time (ΔPTI) depends on the photosynthetically active radiation(PAR), normalized thermal time (TT) and the intercepted fraction of radiation(f_{i-PAR}).

$$\Delta PTI(j) = \left(\sum_{i=1}^{24} TT(i,j)\right) / 24 \times PAR(j) \times f_{i-PAR}(j) \tag{4}$$

where the index i represents hourly calculations, index, j represents daily level, PAR is photosynthetically active radiation which is calculated from the daily global radiation above the crop ($R_g, W\ m^{-2}$).

$$PAR = 0.5 \times R_g \tag{5}$$

TT °C is the normalized thermal time. This concept is used by other researchers like (Bechini et al., 2006; Soltani and Sinclair, 2012;), which is defined as the ratio of the rate of growth under real conditions of optimal temperatures and it is calculated as follows:

$$T = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases} \tag{6}$$

where T_a (°C) is the temperature of the air, $T_{\min}$ (°C) is the minimum temperature, $T_{\max}$ (°C) is the maximum temperature, T_{ob} (°C) is the lower optimal temperature and T_{ou} (°C) is the upper optimal temperature.

The intercepted fraction of the radiation is calculated by the exponential function:

$$f_{i-PAR} = 1 - \exp(-k \times LAI(j)) \tag{7}$$

where k is the light extinction coefficient, and LAI is the leaf area index which it is calculated from the leaf area value A_f (m^2) and depends on the daily photo-thermal time (ΔPTI) by an equation type Michaelis-Menten

$$LAI(j) = \left(\frac{c_1 PTI(j)}{c_2 + PTI(j)} \right) d \tag{8}$$

where c_1 (m^{-2}) and c_2 are parameters of the Michaelis-Menten equation and d ($\mathrm{plants\ m}^{-2}$) is the density of the crop.

The model uses a classical concept approach, efficient radiation application (De Reffye et al., 2009) which allow the calculation of daily increase total DMP (ΔDMP) as a function of the photosynthetically active radiation (PAR) equation (5), crop characteristics such as LAI equation (8) and the radiation use efficiency parameter (RUE, gMJ^{-1}). This approach has been applied by several researchers (Gallardo et al., 2016; Shibu et al., 2010; Soltani and Sinclair, 2012).

$$\Delta DMP(j) = RUE \times f_{i-PAR} \times PAR(j) \qquad (9)$$

The value of (ΔDMP) accumulates day by day as in equation (2). For the purpose of the model, it is not necessary to estimate the partitioning of the DMP in different organs of the plant, since the nutritional extractions of a crop are made from the total biomass produced (Lemaire et al., 2007; Tei et al., 2002a), for purposes of the nutrition management.

Once the daily DMP is calculated, it is possible to calculate the daily Nup by the equation (10, 11) (Tei et al., 2002) an it is accumulated with equation (3), so the calculation of the total nitrogen extraction is obtained throughout the crop growing period (ΔDMP).

$$\%N(j) = a \times \left(DMP(j)\right)^{-b} \qquad (10)$$

$$N_{up}(j) = \left(\%N(j)/100\right) \times DMP(j) \qquad (11)$$

where ΔN_{up} is the daily Nup ($g\,m^{-2}$), a and b are parameters of the equation and $\Delta\, DMP$ is the increase of daily total dry matter produced ($g\,m^{-2}$).

Finally, ETc$(kg\,m^{-2})$ is calculated every hour using the equation proposed by Baille et al. (1994), which has been widely used to schedule irrigations in greenhouse crops (Carmassi et al., 2013; Martínez et al., 2012; Massa et al., 2011). The Baille transpiration model requires the global radiation and the vapor pressure deficit data. VDP is calculated with values of the air temperature, relative humidity, and leaf area index. The equations of the ETc in HortSyst model are described as follows:

$$ETc(i) = A \times (1 - \exp(-k \times LAI(j))) \times Rg(i) + LAI(j) VPD(i) B_{(d,n)} \quad (12)$$

$$ETc(j+1) = \sum_{i=1}^{24} ETc(i) \quad (13)$$

where $ETc(j+1)$ ($kg\, m^{-2} d^{-1}$) is the daily accumulated transpiration, $ETc(i)$ ($g\, m^{-2} h^{-1}$) is the hourly transpiration, R_g is the hourly incident of global solar radiation ($W\, m^{-2}$), VPD is the vapor pressure deficit and A (dimensionless) refers to the radiative parameter; and B_d, B_n ($W\ m^2\ kPa^{-1}$) are parameters of the aerodynamic term of equation (12) for day and night, respectively.

3.2.2 The computational model

The HortSyst is currently programmed in the Matlab computing environment. The dynamic equations are coded inside a Matlab subroutine (function). Two iterative loops allow computing daily and hourly calculations. The outputs of the subroutine are the variables; PTI, total DMP, Nup, ETc, and LAI. The input variables of the subroutine are the model parameters (Table 1) and climatic variables (Figures 3.2 and 3.3). The main program (Matlab script) calls the subroutine and generating graphs or other calculations necessary to run the simulations.

3.2.3 Tomato growth experiments description

The experiment was carried out under greenhouse conditions, during the autumn-winter season, located at the University of Chapingo, Mexico. Geographical location: 19° 29’ NL, 98° 53’ WL and 2240 m. A tomato (*Solanum lycopersicom* L.) crop cultivar "CID F1" was grown in a hydroponic system using volcanic sand as a substrate and it was fertilized with Steiner nutrient solution (Steiner, 1984). Plants were distributed with a density of 3.5 plants m^{-2}. For the experiment, tomato seeds were sown on 18 July 2015 and the plants were transplanted on 21 August 2015 in a type chapel glasshouse with 8 x 8 m dimensions. A HOBO weather station (Onset Computer Corporation) was installed inside of the greenhouse. The air temperature and relative humidity were measured with an S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with an S-LIB-M003 sensor and was located 3.5 m above the ground. Both sensors were connected to a data logger U-30-NRC model in which the environmental variables data were recorded every minute.

Three plants were chosen randomly for the samples each ten days to measure total dry matter, Nup accumulation and LAI. Plants were dried out during 72 h at 70 °C. And nitrogen was determined by Micro-Kjeldahl method. LAI was determined by a nondestructive procedure which consisted of taking four plants randomly in order to get measurements of width and length of the plants' leaves and the total leaf area was measured with a plant canopy analyzer LAI-3100 (LICOR, USA). From the measurements, nonlinear regression models were fitted in order to estimate the LAI. The crop transpiration was measured every minute by means of a weighing lysimeter located in a central row of the greenhouse, the device includes an electronic balance (scale capacity =120 kg, resolution ± 5 g) equipped with a tray carrying four plants. The weight loss measured by the electronic balance was assumed to be equal to the crop transpiration.

Table 3.1. Model parameters used for HortSyst model during greenhouse growing condition.

No	Output	Parameter	Symbol	Units	Nominal Value (autumn-winter)	source
1		Top upper temperature	T_{max}	°C	35.00	Peet & Welles (2005), Chu et al., (2009)
2		Top bottom temperature	T_{min}	°C	10.00	Peet & Welles (2005), Chu et al., (2009)

3		Optimum minimum temperature	T_{ob}	°C	17.00	Peet & Welles (2005)
4	**DMP**	Optimum maximum temperature	T_{ou}	°C	24.00	Peet & Welles (2005)
5		Radiation Use Efficiency	RUE	$g\ MJ^{-1}$	4.01	Gallardo et al., (2014)
6		Extinction coefficient	k	---	0.70	-----
7	**PTI**	PTI initial condition	PTIini	$MJ\ d^{-1}$	0.025	-----
8		N concentration in the dry biomass at the end of the exponential growth period	a	$g\ m^{-2}$	7.55	Gallardo et al., (2014)
	Nup					
9		Is the slope of the relationship	b	---	-0.15	Gallardo et al., (2014)
10		Slope of the curve	c_1	m^{-2}	2.82	Estimated
11	**LAI**	Intersection coefficient	c_2	---	74.66	Estimated
12		Radiative coefficient	A	---	0.3	(Sánchez et al., 2011)
13		Aerodynamic coefficient during day	B_d	$W\ m^{-2}\ kPa^{-1}$	18.7	(Sánchez et al., 2011)
	ETc					
14		Aerodynamic coefficient during night	B_n	$W\ m^{-2}\ kPa^{-1}$	8.5	(Sánchez et al., 2011)

3.2.4 Mode calibration and goodness of fit statistics

The nominal parameters listed in Table 3.1 were used to judge the predictive quality of the HortSyst model. The Bias (BIAS), root mean squared error (RMSE) and Modeling efficiency (EF) statistics (Table 2) were considered to evaluate the performance of simulation of the calibrated and non-calibrated model and also the 1:1 plots between simulated and measured data were used.

An appropriate method to perform model calibration is the nonlinear least squares estimation. A parameters vector p minimize the sum of square errors (Vazquez et al., 2014).

$$\hat{p} = \arg\min J\,(p) \tag{14}$$

$$J(p)=\sum_{h=1}^{L}\sum_{i=1}^{M} w_h\left[\bar{y}_h(t_i,p)-y_h(t_i)\right]^2 \tag{15}$$

Where w_h is the relative weight of each output, $\bar{y}_h(t_i,p)$ is the simulated output, y_h in time t_i , $y_h(t_i)$ is the measurement $y_h(t_i)$ in time t_i, $(L=5)$ is the number of outputs, M is the number of samples during the crop period y_h in time t_i, p is the parameters set of calibration and $\hat{p}$ is the parameter that reduces $J(p)$ to a minimum.

The performance of the non-calibrated and calibrated models was evaluated using the BIAS and the RMSE, and EF statistics was defined as follows (Wallach et al., 2014):

$$BIAS=\left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(Y_i-\hat{Y}_i\right) \tag{16}$$

$$RMSE=\sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(Y_i-\hat{Y}_i)^2} \tag{17}$$

$$EF=1-\frac{\sum_{i=1}^{N}\left(Y_i-\hat{Y}_i\right)^2}{\sum_{i=1}^{N}\left(Y_i-\bar{Y}_i\right)^2} \tag{18}$$

where the number of measurements is N, $\boldsymbol{Y_i}$ is the measured value for situation i and $\bar{Y}_i$ is the corresponding value predicted by the model.

3.3 Results

3.3.1 Simulation of HortSyst Model

3.3.1.1 Input variable

The global solar radiation (Rg), air temperature (Ta), and relative humidity (RH) used in the simulations of the HortSyst model for the season autumn-winter are shown in Figure 3.2 and 3.3. The nominal values of the model parameters are given in Table 3.1. According to the measured data of Figure 3.2, it is clear that the amount of global radiation accumulated in the autumn-winter season is too low, because of the rain period and so most of the days are cloudy. In addition, likely the type of greenhouse where the experiment was carried out has a strong effect on the radiation interception, because of the cover of shade placed on the roof of the greenhouse, the highest daily value measured of the global radiation was 8.89 MJ m^{-2} d^{-1}, the average was 3.99 m^{-2} d^{-1} and the minimum value of 0.88 m^{-2} d^{-1}.

Figure 3.3 shows the daily average of the air temperature and relative humidity during the crop cycle, the maximum temperature measured was 21.83 ^{o}C, the mean was 18.31 ^{o}C and the minimum of 14.12 ^{o}C and for HR the maximum recorded value was 93.98%, the average was 78.58% and the minimum of 62.59% during the whole crop cycle. The low level of radiation and temperature recorded has its effect on the reduction of the accumulation of total DMP, Nup, and LAI, for this season and the high values of RH reduce the VPD and this affects directly on the ETc of the crop.

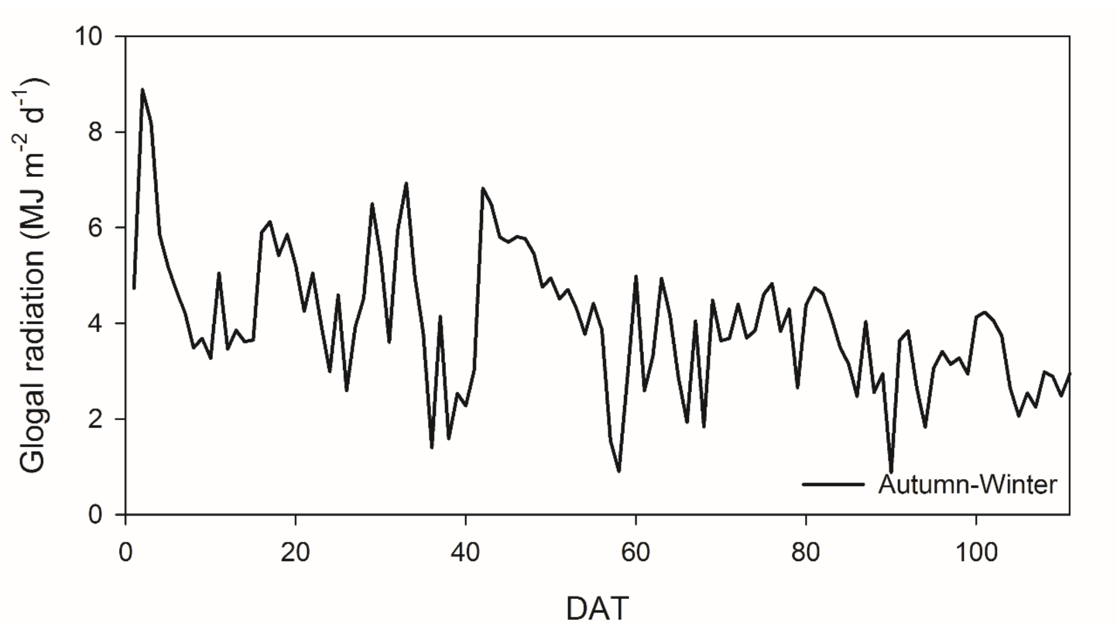

Figure 3.2.The daily average global radiation measured inside of the greenhouse located in Chapingo, Mexico during autumn-winter season, 2015

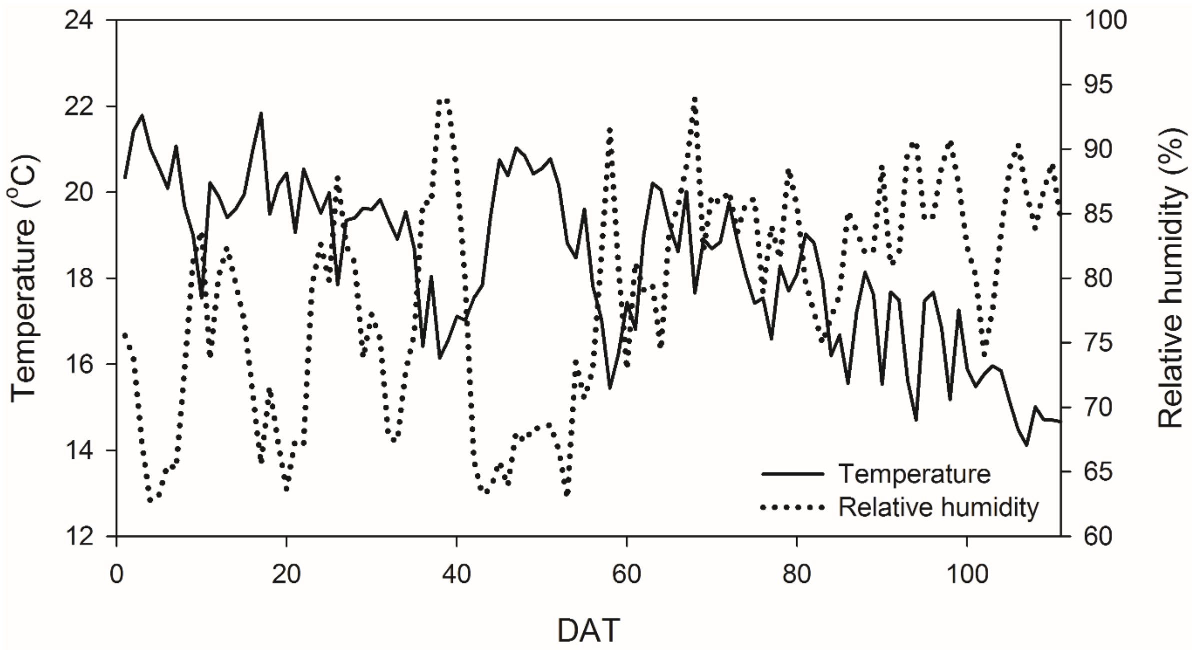

Figure 3.3.Air temperature and relative humidity daily average measured inside of the greenhouse, located in Chapingo, Mexico, during autumn-winter season, 2015

3.3.1.2 Dry matter Production (DMP)

Figure 3.4a shows the simulations of DMP by the HortSyst model with and without calibration. The RUE nominal value was 4.01 g MJ^{-1} (Gallardo et al.,2014), and the value of RUE resulted from calibration was 4.86 g MJ^{-1}. It was found that the simulations follow the trend of the measured values in the laboratory. The accumulated values of total DMP simulated at end of the crop cycle without calibration of 587.370 g m^{-2} and the calibrated value of 697.290 g m^{-2} against a measured value of 673.380 g m^{-2}. According to the statistics showed in Table 3.2 the BIAS value of the non-calibrated model simulations indicates that exists an under-estimation of the predicted values and conversely, for the calibrated model the BIAS indicates a slightly over-estimation of the predicted values of the model. The reduction of the RMSE between the non-calibrated and calibrated model was more that three times. The EF values also improved significantly when the model was calibrated, as it can see in Figure 3.4a at a glance how the model estimations and measurements correspond. This is also confirmed by the 1:1 plot showed in Figure 3.4b. In the experiment, total DMP shows firstly an exponential growth and then an approximately linear growth phase, which is a growth pattern expected.

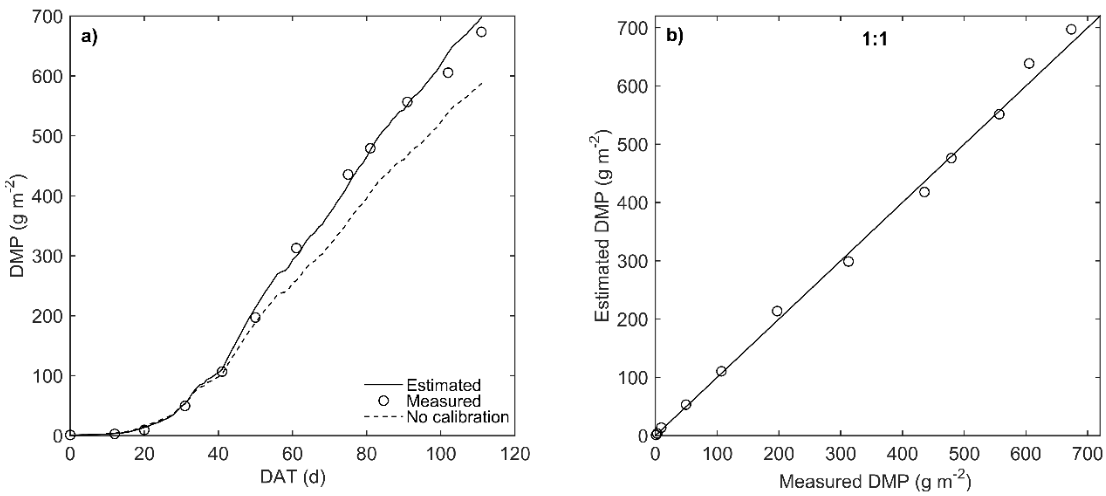

Figure 3.4. Time course of the simulated and measured values of total DMP with and without calibration of the HortSyst model of a greenhouse tomato crop grown in Chapingo, Mexico, b) 1:1 plot for simulated values by the calibrated model and measured values

3.3.1.3 Nitrogen Uptake (Nup)

Figure 3.5a shows a comparison between the measured and predicted values by the HortSyst model, for the Nup during the crop cycle. In this case, a satisfactory fit between the simulations and measurements is observed for this output, the accumulation of the Nup at the end of the crop predicted by the simulation with the non-calibrated and calibrated model were 19.960 g m^{-2} and 14.466 g m^{-2}, respectively against the measured value of 13.71 g m^{-2}. The calibrated parameters of this variable were (a = 5.850 and b = -0.190). According to the statistics values (Table 3.2) the BIAS the model over-estimate Nup in case of non-calibrated and calibrated model. However, the BIAS close to zero obtained by the calibrated model means that the quality of prediction improved considerably by calibration. In fact the RMSE value decrease more that six times after calibration. Also the EF values improved from 0.6 to 0.9. The Figure 3.5 b) shows accurate predictions of Nup by HortSyst model.

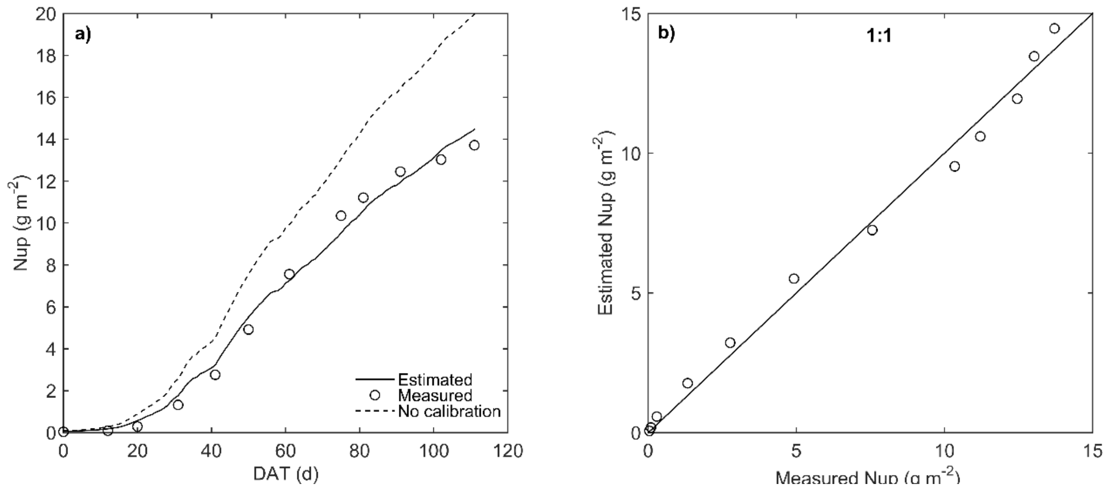

Figure 3.5.Time course of the simulated and measured values of Nup with and without calibration of the HortSyst model of a greenhouse tomato crop grown in Chapingo, Mexico, b) 1:1 plot for simulated values by the calibrated model and measured values

3.3.1.4 Leaf Area Index (LAI)

Because a lack of information in the literature for the parameters of this variable (c_1 and c_2) a manual calibration was carried out in order to determine the possible values that could be used in the simulation for the growing period, this means that a pre-calibration was carried out using the Matlab programming software to fit the leaf area versus PTI separately of the whole HortSyst model. The LAI variable plays a central role in the model since, from this variable simulated the PTI, DMP and ETc are predicted. The considered values of the parameters (c_1 and c_2) are shown in Table 3.1. The cumulative LAI values of the simulation at the end of the crop cycle for non-calibrated and calibrated model are quite similar to the measured these were 5.850 m^2 m^{-2}, 5.785 m^2 m^{-2}, and 5.780 m^2 m^{-2}, respectively. The calibrated parameters of LAI were c1 (2.649) and c2 (63.461). According to the statistics BIAS, RMSE and EF showed in Table 3.2 the performance behavior of the model with the pre-calibration and the calibration are the same which means that the local calibration of the LAI sub-model had no effect on the global calibration of the VegSyst model. The small values for BIAS and RMSE and the EFF value of 0.99 indicates that the LAI predictions follow accurately the measurements (Figure 3.6b).

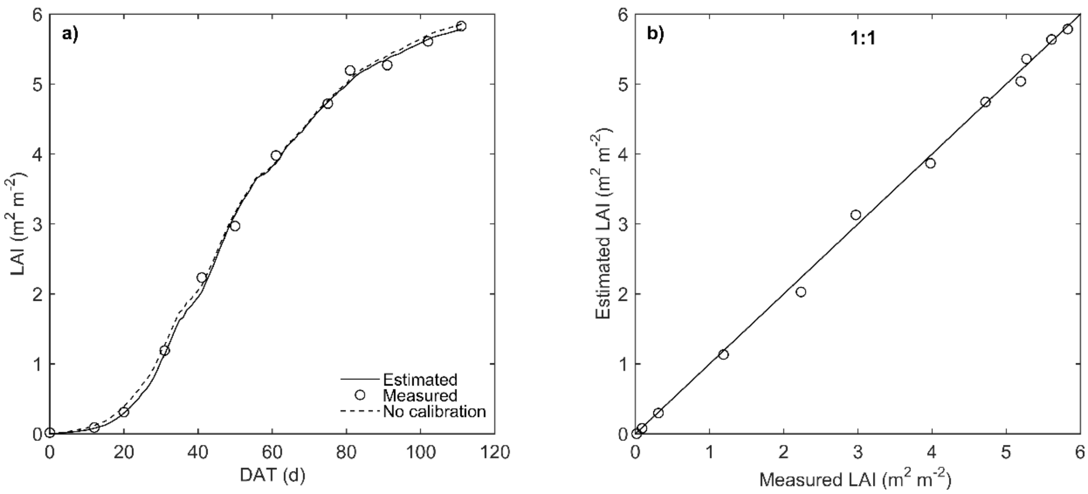

Figure 3.6. Time course of the simulated and measured values of LAI with and without calibration of the HortSyst model of a greenhouse tomato crop grown in Chapingo, Mexico, b) 1:1 plot for simulated values by the calibrated model and measured values

3.3.1.5 Crop transpiration rate (ETc)

For the ETc variable in Figure 3.7a, using the parameter values shown in Table 3.1 for A, Bd, and Bn it was found that the goodness of fit statistics using the parameters of the literature was not satisfactory. So that fact justifies the calibration of the model, with the goal of greatly improving the statistics, these parameters changed with the calibration for A (0.628), Bd (28.571) and Bn (5.0). According to the BIAS statistic the calibrated model improve more than six times. The RMSE was also smaller in case of the calibrated model. And the modelling efficiency also got better (Table 3.2). The water uptake accumulated at the end of crop production for non-calibrated model was 108.970 kg m^{-2}, calibrated was 197.262 kg m^{-2} and measured was 183.68 kg m^{-2}. The calibrated simulation slightly underestimates the ETc before 50 DAT and overestimates after the days 50 DAT (Figure 3.7b), so when the crop has less than 3 m^2 m^{-2} of LAI, the prediction is accurate. To apply the model in the scheduling of irrigation it is necessary to evaluate the ETc hourly. A comparison of the measured and predicted transpiration by the calibrated HortSyst model is showed (Figure 3.8).

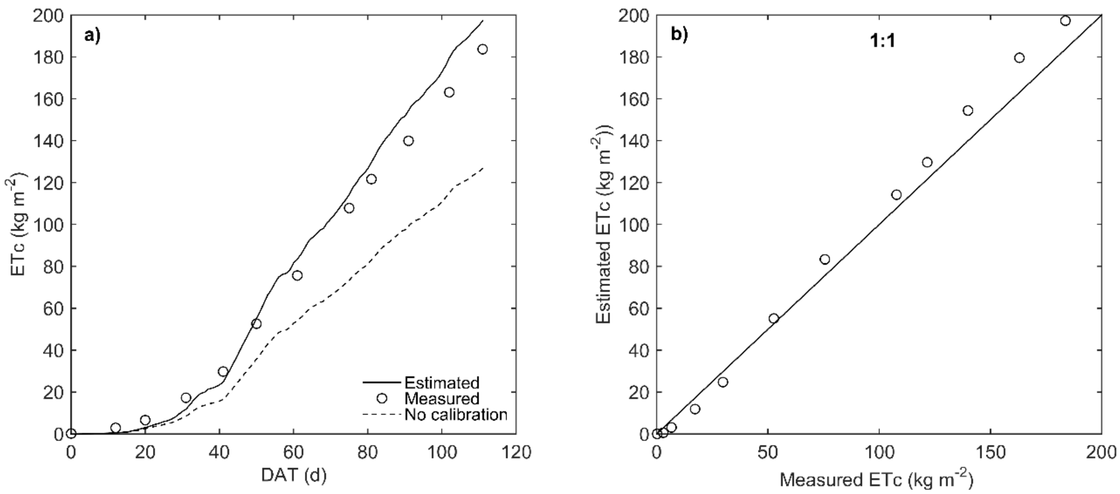

Figure 3.7.Time course of the simulated and measured values of ETc with and without calibration of the HortSyst model of a greenhouse tomato crop grown in Chapingo, Mexico b) 1:1 plot for simulated values by the calibrated model and measured values

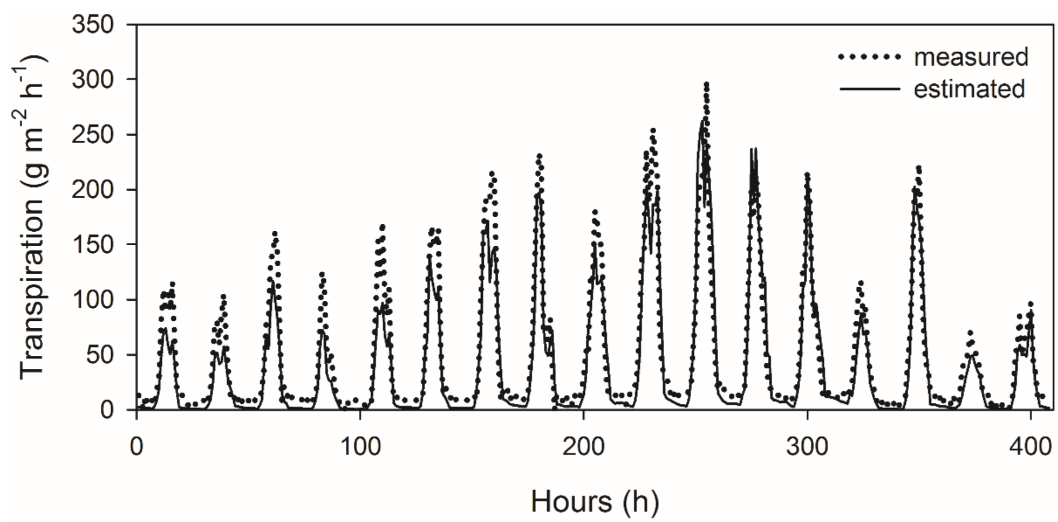

Figure 3.8.Time course of the simulated and measured values of ETc calibrated from 13 to 30 September 2005 of a greenhouse tomato crop grown in Chapingo, Mexico

3.3.1.6 Photo-thermal time (PTI)

Figure 3.9a shows the PTI variable that is used by the HortSyst model to calculate the LAI. PTI behavior is similar to the one reported by Xu et al. (2010). Figure 3.9b shows the relationship between PTI and LAI through a Michaelis-Menten type function. This PTI model gave a satisfactory prediction of LAI, using the temperature and PAR radiation data, the parameter that was calibrated for this variable was the initial condition PTIini (0.013 $MJ\ d^{-1}$).The amount of PTI accumulated in autumn winter was 105.271$MJ\ d^{-1}$. The HortSyst model simulates PTI and LAI during the crop cycle this is the main differences between other models like VEGSYST and CROPSYST models (Stockle et al., 2003).

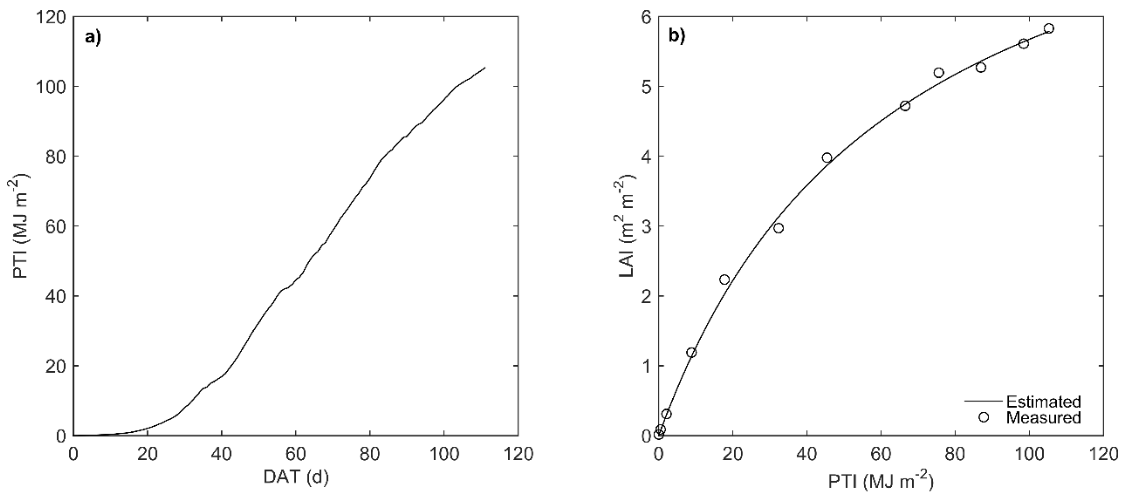

Figure 3.9.Time course of the predicted of PTI by HortSyst model, accumulated from day after transplant for autumn-winter b) relationship between PTI vs LAI

Table 3.2. Summary of the results of the statistical indices; BIAS, RMSE and EF used to evaluate the performance of the HortSyst model simulation for DMP, Nup, ETc, and LAI during autumn-winter, 2015.

	HortSyst no calibration	HortSyst Calibrated		HortSyst no calibration	HortSyst Calibrated
Statistics	**DMP (g m^{-2})**		**Statistics**	**LAI (m^{-2} m^{-2})**	
BIAS	37.443	-3.897	BIAS	-0.028	0.026
RMSE	53.599	14.543	RMSE	0.099	0.100
EF	0.952	0.996	EF	0.998	0.998
	Nup (g m^{-2})			**ETc (g m^{-2}h^{-1})**	
BIAS	-2.551	-0.071	BIAS	20.618	3.647
RMSE	3.179	0.500	RMSE	46.417	39.330
EF	0.635	0.991	EF	0.743	0.815

Figure 3.10 shows the daily Nup concentration, predicted by the model in order to show a potential use of the HortSyst model to predict the concentration of

Nup of the crop as a function of the ETc for the autumn-winter crop cycle. As can be seen in Figure 3.10 during the first 20 days after transplant (DAT), the Nup concentration by crop exceeds the concentration of 12 me L^{-1} (168 mg L^{-1}) recommended by Steiner, (1984), from 20-50 DAT the concentration decreases gradually from 12-6 me L^{-1} and finally after 50 DAT the concentration decreases approximately up to less of half of the recommended concentration. With the evaluation of the performance of the model, it was found that with model application it would be having a saving of approximately 50% of the applied fertilizer considering an efficiency of 100% of the system production under soilless culture this mean a management with zero drainage.

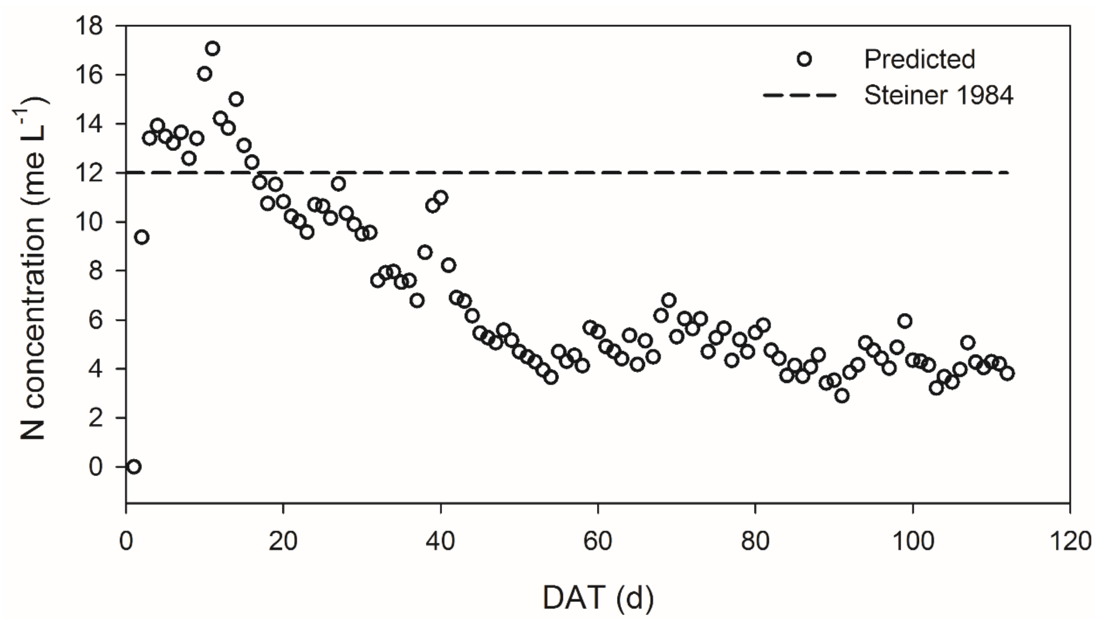

Figure 3.10.Time course of simulation of daily value of N concentration (me L-1) nitrogen uptake during autumn-winter, 2015.

3.4 Discussion

HortSyst model predicts correctly DMP, PTI and predicts accurately LAI, however, the quality of prediction of Nup and ETc is poor using the nominal values of its parameters. This means that after calibration the model improved the predictive quality not only for Nup or ETc also for the parameter of the other output variables estimation by using experimental data. Because of the results obtained in the simulation using the RUE value of 4.01 g MJ^{-1} reported by

Gallardo et al.(2016) for prediction of DMP the quality of the simulated values is quite acceptable but was necessary to carry out the calibration to find the exact value of RUE. For this output at the end of the cycle are slightly lower than those reported by Gallardo et al. (2014) for autumn-winter. The value of RUE of 4.867 g MJ^{-1} (d= 3.5 plant m^{-2}) from the model calibration is higher than 4.1 g MJ^{-1} for density of 2.0 plant m^{-2} reported by Gallardo et al. (2014), and the value 3.0 g MJ^{-1} for winter and summer found by Challa and Bakker (1999), 1.05 g MJ^{-1} for the same season with 1.1 plant m^{-2} of density crop according to Scholberg et al. (2000) and 1.89 – 2.44 g MJ^{-1} (Tei et al., 2002a). These values of RUE are probably different due to differences in climatic conditions between one region and another and the management of the culture (Cota et al.,2014.). Also RUE is affected by vapor pressure (Kemanian et al., 2004) and abiotic factors as drought, low temperatures (Soltani and Sinclair, 2012) and nutrients availability, the crop growing location and the crop varieties (Muurinen and Sainio, 2006). Furthermore, of all plant nutrients, nitrogen is the one that most influences on RUE parameter. The RUE value comparison between species with respect to photosynthetic processes indicates that C4 species have higher RUE than C3 species (Muurinen and Sainio, 2006).

The amount N extracted by the tomato crop as a result of the calibrated model at the end of the cycle was 14.466 g m^{-2} is the half of the quantity (30 g m^{-2}) of the spring-winter season reported by Gallardo et al., (2014), 25 g m^{-2}-28 g m^{-2} found by Tei et al. (2002a) and 25-35 g m^{-2} by Elia and Conversa, (2012) and approximately close to the measured value by (Pineda-Pineda et al., 2009). The difference in the values accumulated for Nup at the end of the crop cycle is because in each cycle the environmental conditions are not the same at least in the levels of radiation because of the location and maybe the temperature variation between the day and night. In this case, the model did not show a satisfactory fit for without calibration, but with the calibration, it reached all measured data. The calibrated parameters of the nitrogen content were a = 5.850 and b = -0.190; this means that there is a decline in N% with an increase of DMP and it follows a similar pattern across a range of crops. The value of the parameter a is smaller than a = 7.55 found by Gallardo et al. (2014) and a = 2.29–5.41 found by Tei et al. (2002a), the b parameter from the calibration was slightly higher than b= -0.15 (Gallardo et al., 2014) and lower than b = -0.25 and -0.36 (Tei et al., 2002b). These differences in the parameters are probably the variety of crops, season, environmental condition and the management of the culture systems.

The modeling of LAI is one of the important differences of the HortSyst model with respect to the VEGSYST model since this variable was not included in VegSyst model. However, the relevance of LAI in crop growth models has been recognized by several researchers (Goudriaan and van Laar, 1994; Wallach et al., 2014; Thornley and France, 2007; Soltani and Sinclair, 2012). As a matter of fact, to improve the performance of a new model it is important to include this variable as state or auxiliary variable.

The final accumulated of the ETc by calibration process value for the autumn-winter was 197.262 kg m^{-2} is close (~200 mm) at 110 DAT reported by Gallardo et al. (2014, 2016) and by Zotarelli et al. (2009). It is important to mention that the methodology to model water consumption by Gallardo et al. (2014, 2016) was different since they used the Penman-Monteith model with growth coefficients the disadvantage of using this approach is that does not allow to schedule the irrigation in soilless culture because in these systems are needed providing the irrigation with high frequency and low flow irrigation. The calibration for A was 0.628, Bd (28.571) and Bn (5.0). The value of the parameter A from calibration is lower than A = 0.946 found by (Massa et al., 2011) and higher than A = 0.372 mentioned by Martínez et al. (2012) and closer to A = 0.59 reported by Montero et al. (2001). The Bd and Bn parameters are lower than B = 30 (Martínez et al., 2012) and higher than Bd (19.1) reported by Medrano et al. (2008) and Sánchez et al. (2011) the values of the Bn resulted much lower than (Bn = 26.0) found by Medrano et al. (2008), and slightly lower of Bn = 8.5 (Sánchez et al., 2011). The difference between parameters of the calibration against the parameter values found in the literature reviewed is that the times of simulations of the ETc, because in each research are different. The model of transpiration used in HortSyst model according to Medrano et al. (2005) who calibrated this model for a cucumber crop for spring-summer and autumn-winter found that for the autumn winter season the model does not fit very well. This , fact agrees with the results that are presented in this research the problem is due to the low level of radiation and VPD during this crop season.

In the case of PTI, Xu et al. (2010) found that modeling the LAI using this concept provides better predictions than using the thermal time concept alone. The models based on thermal time could overestimate or underestimate the predictions of LAI because of the fact that inside of the greenhouse the global radiation is not synchronized with the temperature behavior inside of the greenhouses (De Reffye et al., 2009; Xu et al., 2010). On the other hand, when comparing the estimation of LAI using the specific leaf area as used in (Stockle et al., 2003) presents a poor prediction due to the large variation of the specific leaf area between different growing seasons and the data of this latter variable can only be obtained by destructive measurements. This can limit the application of models based on specific leaf area of greenhouse crops and climate management practice (Xu et al., 2010).The advantage of using a mathematical model to make fertilization recommendations is that it considers factors as; environmental conditions, physiological processes such as ETc and characteristics of the crop as LAI and DMP. The results show that with the developed model with parameters estimated the simulations of N concentration turned out to be quite similar to those reported by Gallardo et al. (2014) for the Autumn-winter season, who evaluated the use of the model VEGSYST under three scenarios of the recommendation of fertilization.

3.5 Conclusions

Excellent predictive quality for DMP, Nup, LAI, and ETc provides the simulation carried out by HortSyst model with the parameters estimated. This is confirmed by the quality of the predictions shown in the previous figures and the statistic values of BIAS, RMSE, and EF found in this research and with the calibration of the model were found the optimum values of the parameters that attain the best fit between predictions and measurements for autumn-winter season for tomatoes crop under soilless culture. The calibration of the HortSyst model was successful to find these values of the parameters that helped to improve its predictive quality. The HortSyst model can be used as a decision-making tool in greenhouse production systems since according to the presented simulation, it predicts in an accurate way the total DMP, Nup, LAI, and ETc. In order to model the LAI, a new concept called the PTI, which represents the effect of temperature on leaf expansion and the effect of radiation on crop growth, may be used in crop models. In fact, there are few models that include the variable ETc in order to be used in irrigation management, in this case, was used a model that was derived from the simplification of Penman-Monteith was used and its simplicity it can be used to predict the consumption of water by the crop. Furthermore, it needs climatic variables that are commonly measured in greenhouses. However, more research is needed to improve the ETc model predictions for the Autumn-winter cycle when the levels of radiation and VPD are low. However, it is necessary carrying out an evaluation of the model, with data from another experiment in a different crop cycle to evaluate its behavior under different scenarios. Due to the small number of parameters (thirteen parameters) involved in the HortSyst model, it is feasible to use it for irrigation management and nitrogen application in hydroponic tomato under greenhouses.

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4. QUANTIFYING UNCERTAINTY IN HORTSYST CROP GROWTH MODEL PREDICTIONS, FOR FERTIGATION OF TOMATOES IN GREENHOUSE SOILLESS CULTURE

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Abstract

The HortSyst is a new nonlinear dynamic growth model for hydroponic systems, for tomatoes grown in greenhouses without any water and nutrient limitations. The aim of this research was to determine the uncertainties of outputs model predictions because of the uncertainty of the model parameters variation with 10 and 20%. It was assigned a uniform probability density function to the parameters and a Latin Hypercube sampling (LHS) was used. Both a frequentist uncertainty analysis procedure and also the Generalized Likelihood Uncertainty Estimation (GLUE) methods were used. Two experiments were carried out under greenhouse conditions, during the season autumn-winter and spring-summer. For probability distributions analysis of output variables; the minimum, maximum, mean, Skewness, and Kurtosis values besides histograms, confidence intervals, RMSE, and scatterplots were analyzed. According to the results obtained by the frequentist UA the model predictions are reliable. The 95% confidence intervals calculated by the GLUE procedure confirmed this observation and additional it could be an important tools to parameter estimation of the model.

Keywords: model simulation, transpiration, potential growth, nitrogen management

4.1 Introduction

Several models have been developed during the last two decades for simulation of the growth and development of a tomato crop, but only a few of them simulate growth, development and yield. One of the main objectives of these models is their use as a tool for optimizing greenhouse climate control and the evaluation of management practices (Cooman and Schrevens, 2006). Integrating environmental models have emerged as useful tools supporting research, policy analysis, and decision making (Matott et al., 2009). Crop models have been developed to simulate the complex interactions between crop management, soil, and atmosphere, to make the prediction of crop yield and environmental impacts of cropping systems. Because of, the yield formation depends on dry matter production, crop development strongly interacts and may be affected by water and nutrient limitations. These interactions are particularly complex in species that exhibit an indeterminate growth pattern such as tomatoes in which new flowers are continuously being produced for a certain amount of time as far as environmental conditions remain favorable (Valdés et al., 2014).

The HortSyst is a new nonlinear dynamic growth model for hydroponic systems, for tomatoes (*Solanum lycopersicom* L.) grown in greenhouses. This model was developed to be used as a tool for decision support systems and assumes that crops have no water and nutrient limitations. The HortSyst model predicts crop dry matter production, N uptake and photo-thermal time as state variables and crop transpiration and leaf area index as output variables. HortSyst model was developed based on VegSyst model (Gallardo et al., 2011; Gallardo et al.,2014; Gallardo et al.,2016; Giménez et al., 2013; Granados et al., 2013). It has thirteen parameters. A common approach to decision support based on a model, define the boundaries of the system and its structure, the elements, and the link flows and the relationship between these elements (Walker et al., 2003) to explain the cause-effect relationships characteristics of the systems.

In a mathematic model, the relationships between the components of the system are expressed as functions, and then a computer program makes a translation of this mathematical model into computer code in decision support activities.

Thus, the focus of a modeling exercise is typically on the response of a system to outside forces. To evaluate the system's simulation (resulting values of the outcomes of interest) many analytical tools have been used to deal with the uncertainties of the unknown and unknowable future (Walker et al., 2003). Uncertainty assessment of model simulations is therefore, important, for example, when the model is used to support water and nutrient management decisions, for integration of model results into the broader water and nutrient management process and to increase the effectiveness of knowledge production and use. Refsgaard et al. (2005) have emphasized the relevance of performing an uncertainty analysis on a going theme from the beginning with problem definition and identification of modeling objectives and then throughout the modeling process. In order to be most useful, the decision support model should also include information about the uncertainties related to each of decision options, as uncertainty of the desired outcomes may be the central criterion for the selection of the management policy (Uusitalo et al., 2015; Wallach et al., 2014) . Several researchers have described uncertainty as manifesting itself at the different location in the model based on the water management process (Gal et al., 2014; Helton et al., 2005; Walker et al., 2003; Wallach et al., 2014). This location, or sources, may be characterized as follows; i) context and framing (at the boundaries of the systems to be modelled), ii) inputs (external driving force and system data that drive the model, climate data), iii) model structure (is the conceptual uncertainty due to incomplete understanding and simplified description of modelled process), iv) parameter (the uncertainty related to parameter value), v) model technical (is the uncertainty arising from computer implementation of the model, due to numerical approximation resolution in space and time, and bugs in the software). Several methodologies and tools suitable for supporting uncertainty assessment have been developed and reported in the scientific literature, these methods represent the commonly applied types of methods and tools, such as: Data uncertainty engine, error propagation equations, expert elicitation, extended peer review, inverse modeling, Monte Carlo analysis, multiple model simulation, multidimensional uncertainty assessment, quality assurance, scenario analysis, sensitivity analysis, Stakeholder involvement, uncertainty matrix and Bayesian approach (Refsgaard et al., 2007) .There are few studies that report the type of frequentist uncertainty analysis (Monte Carlo) applied to crop models specifically in greenhouses, some of these are the TOMGRO model applied for tomato (Cooman and Schrevens, 2006), or the NICOLET model for lettuce crop (López et al., 2012), most of the researches has focused on open field crops, for example the uncertainty analysis applied to the CERES-maize model described by Bert et al. (2007) and Li et al., (2012), SALUS model for maize, Peanut and cotton (Dzotsi et al., 2013), and the WARM rice model (Confalonieri et al., 2016). The uncertainty analysis applying Bayesian methods is still less common even for open field crops, for example Iizumi et al. (2009) studied the uncertainty using the Bayesian approach for the SIMRIW model for paddy rice, and Pathak et al. (2012) used the GLUE procedure (Bayesian approach) for CSM-CROPGROW-Cotton model.

The aim of this research was carried out an uncertainty analysis of the HortSyst model parameters. These were considered fixed at the time. The uncertainty of output variables was defined as the variation caused by the output quantified by its variation coefficient, when the parameters were varied 10% and 20% around its nominal values, assigning them a uniform probability density and using Latin Hypercube Sampling (LHS), with frequentist uncertainty (Monte Carlo) method and Generalized Likelihood Uncertainty Estimation (GLUE) methods for autumn-winter and spring summer crop season.

4.2 Material and methods

4.2.1 Greenhouse condition and data acquisition

Two experiments were carried out under greenhouse conditions, during the autumn-winter, and spring-summer season, located at the University of Chapingo, Mexico. Geographical location: 19° 29’ NL, 98° 53 WL and 2240 m. Two tomatoes (*Solanum lycopersicom* L.) crop cultivar "CID F1" were grown in hydroponic systems using volcanic sand (Tuff) as a substrate. Plants were distributed with a density of 3.5 plants m^{-2}. For the first experiment, tomato seeds were sown on 18 July 2015, and the plants were transplanted on 21 August 2015, in a type chapel glasshouse with 8 x 8 m dimensions. The second experiment the seeds were sown on 24 March 2016 and transplanted on 24 April 2016, in a plastic greenhouse with natural ventilation with dimensions of 8 x 15 m. Both experiments were fertilized with Steiner nutrient solution (Steiner, 1984). A HOBO weather station (Onset Computer Corporation) was installed inside of the greenhouses. Temperature and relative humidity were measured with an S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with an S-LIB-M003 sensor located at 3.5 m above the ground. Both sensors were connected to a data logger U-30-NRC model, and the data were recorded every minute, and subsequently the data were processed to obtain average data at hourly intervals.

In each experiment, three plants were chosen randomly for the sampling of each ten days to measure dry matter, nitrogen uptake, and leaf area index. The plants were dried out during 72 h at 70 °C in an oven. Nitrogen was determined by the Kjeldahl method. The leaf area index was estimated by a nondestructive method which consisted in taking four plants randomly in order to get measurements of width and length of the plant's leaves and also the total leaf area and a plant canopy analyzer LAI-3100 (LI-COR, USA) was used. From the measurements, nonlinear regression models were fitted in order to estimate this variable. This due to the plants sampled during the measurement of the transpiration had to be kept alive until to end of the experimental phase. The crop transpiration was measured every minute by a weighing lysimeter located in a central row of the greenhouses. The device includes an electronic balance (scale capacity =120 kg, resolution ± 0.5 g equipped with a tray carrying four plants for both experiments. The weight loss measured was assumed to be equal to the crop transpiration.

4.2.2 Model Description

The dynamic HortSyst model (Martinez et al., 2017) assumes that the crop have no water and nutrient limitations, and it simulates Photo-thermal time (PTI, MJ d^{-1}), dry matter production ($DMP,$ g m^{-2}), Nitrogen uptake ($Nup,$ g m^{-2}), as the state variables besides the leaf area index ($LAI,$ m^{2} m^{-2}) and crop transpiration (ET_c, kg m^{-2}) as output variables. In Table 1 are listed the mathematical equations of the three-state variables and the two output variables. Figure 1 shows the general structure of the model using a Forrester diagram. The model structure is based on VegSyst model developed by (Gallardo et al., 2011; Gallardo et al., 2016; Gallardo et al.,2014; Giménez et al., 2013). The input variables of the model are hourly measurements of air temperature (°C) Figure 2, relative humidity (%) Figure 3, and integration of solar radiation (Wm^{-2}) Figure 4. The models with the light (radiation) use efficiency approach (Kang et al., 2008; Lemaire et al., 2008; De Reffye et al., 2009) which allows the calculation of daily dry matter production (ΔDMP) Eq. (8) as a function of the photosynthetically active radiation (PAR) Eq. (9), crop characteristics such as leaf area index (LAI) Eq. (10) and the radiation use efficiency parameter (RUE, g MJ^{-1}) as has been proposed by several researchers (Shibu et al., 2010; Soltani and Sinclair, 2012). The fraction of light intercepted (f_{i-PAR}) formalism of light intercepted relies upon the leaf area index (LAI), which is the total functioning leaf area for a unit surface area of ground covered by the plant population. The extinction coefficient (dimensionless k parameter) is related to leaf size and leaf orientation; this assumption is usually robust and tolerates some shift for reality. Leaf area index (LAI), was modelled as a function of Photo-thermal time (PTI) using the Michaelis-Menten equation and is multiplied by the density of planting d to obtain the leaf area index(LAI). For this purpose, it has calculated the normalized thermal time (TT, °C) with Eq. (6) and it is defined as the ratio of the growth rate under conditions of actual and optimum temperature conditions according to Dai et al. (2006).Then daily Photo-thermal time (ΔPTI) Eq. (5), is calculated as the product of normalized thermal time with the fraction of light intercepted(f_{i-PAR}) and PAR radiation, then the accumulation of PTI is calculated as Eq. (1) (Xu et al., 2010).

For daily nitrogen uptake ΔN_{up}, first the nitrogen content $\%N$ is calculated with the exponential model (Tei et al., 2002) eq. (11). And it is a function of the daily dry matter production (ΔDMP) and uptake nitrogen is simulated by Eq. (12). Then its accumulated value is given by eq. (3). Finally, the crop transpiration (ETc) is computed hourly, with Global radiation, vapor pressure deficit, the fraction of light intercepted and leaf area index as shown in eq. (14). And it is accumulated with equation (4).

Table 4.1. HortSyst model equations

Variable	Definition	Equation		Units
$\boldsymbol{PTI}$	Photo-thermal time	$PTI(j+1) = PTI(j) + \Delta PTI$	(1)	$MJ\ m^{-2}$
$\boldsymbol{DMP}$	Dry matter production	$DMP(j+1) = DMP(j) + \Delta DMP$	(2)	$g\ m^{-2}$
$\boldsymbol{N_{up}}$	Nitrogen Uptake	$N_{up}(j+1) = N_{up}(j) + \Delta N_{up}$	(3)	$g\ m^{-2}$
$\boldsymbol{ETc}$	Daily crop transpiration	$ETc(j+1) = ETc(j) + \Delta ETc$	(4)	$kg\ m^{-2}$
$\Delta\boldsymbol{PTI}$	Daily photo - thermal time	$\Delta PTI(j) = \left(\sum_{i=1}^{24} TT\ (i,j)\right) PAR(j) \times f_{i-PAR}(j)$	(5)	$MJ\ m^{-2}\ d^{-1}$
$\boldsymbol{TT}$	Normalized Thermal Time	$TT = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases}$	(6)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\boldsymbol{PAR}$	PAR	$PAR(j) = 0.5 \times R_g$	(7)	$MJ\ m^{-2}$
$\Delta\boldsymbol{DMP}$	Daily dry matter production	$\Delta DMP(j) = RUE \times f_{i-PAR}(j) \times PAR(j)$	(8)	$g\ m^{-2}$
$\boldsymbol{f_{i-PAR}}$	Intercepted PAR fraction	$f_{i-PAR} = 1 - \exp(-k \times LAI(j))$	(9)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\boldsymbol{LAI}(\boldsymbol{j})$	Leaf Area Index	$LAI(j) = \left[\frac{c_1 \times \Delta PTI(j)}{c_2 \times \Delta PTI(j)}\right] \times d$	(10)	$m^2\ m^{-2}$
$\%\boldsymbol{N}(\boldsymbol{j})$	Nitrogen content	$\%N(j) = a \times (\Delta DMP)^{-b}$	(11)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\Delta\boldsymbol{N_{up}}$	Daily Nitrogen Uptake	$N_{up}(j) = (\%N(j)/100) \times DMP(j)$	(12)	$g\ m^{-2}$

$\boldsymbol{ETc(i)}$	Hourly Transpiration	$ETc(i) = A \times (1 - \exp(-k \times LAI(j))) \times Rg(i) + LAI(DPV)B_{(d,n)}$	(13)	$kg\ m^{-2}\ h^{-1}$
$\boldsymbol{ETc(j)}$	Daily Evapotranspiration	$\Delta ETc = \sum_{i=1}^{24} ETc(i)$	(14)	$kg\ m^{-2}$

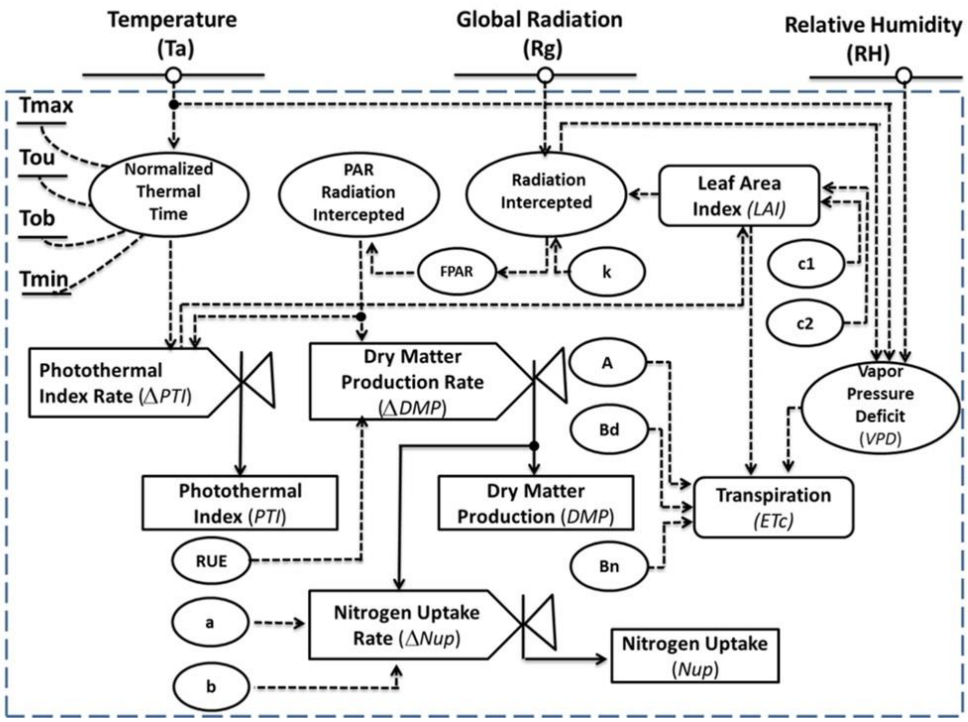

Figure 4.1. Forrester diagram for the HortSyst crop Model with three state variables

4.2.3 Monte Carlo uncertainty Method

According to Refsgaard et al. (2007), Monte Carlo simulation is a statistical technique for stochastic model calculations and analysis of error propagation in calculations. Its purpose is to trace out the structure of the distributions of the model output. In its simplest form, these distributions are mapped by calculating the deterministic results (realizations) for a large number of unbiased random draws (Matott et al., 2009) from the individual distribution function of input data and parameters of the model. As in random Monte Carlo sampling, pre-existing information about correlations between input variables can be incorporated. Monte Carlo analysis requires the analysis to specify probability distributions of all inputs and parameters and the correlations between them. Both probability distributions and correlations are usually poorly known. Ignoring correlations and covariance in input distributions may lead to substantial under or over-estimation of uncertainty in the model outcome. Advanced sampling methods have been designed such as Latin Hypercube sampling (LHS) methods to reduce the required number of model runs needed to get sufficient information about the distribution on the outcome (mainly to save computational time). The stratified sampling (Matott et al., 2009) divides a given input distribution into intervals. For efficient sampling, intervals, typically are constructed so that each has an equal probability of occurrence.

According to Monod et al. (2006), an uncertainty analysis consists of the following steps.

Step 1. Specification of probability distribution functions of the input factors, since no additional information was available, in a first approach, a uniform probability density function was selected for each of one of the HortSyst model's parameters the lower and upper limits of the uncertainty intervals were defined regarding a 10% and 20% of the parameter variation around its nominal value (Table 2) which was taken from Gallardo et al. (2014), Heuvelink, (1999), Medrano et al. (2005), and Medrano et al. (2008) for the season spring-summer.

Step 2. Value generation for input factors. The input factors were the HortSyst model's parameters (Table 2). Latin Hypercube sampling was applied to generate N=10,000 values for each one of the parameters analyzed using a subroutine that was programmed in the Matlab programming environment.

Table 4.2. Description of the HortSyst parameters with 10% of variation of their nominal value, used for uncertainty simulation under experimental condition for spring and summer seasons.

No	Parameter	Symbol	Nominal Value	Lower Limit	Upper Limit
1	Top upper temperature (°C)	T_{max}	35.00	31.50	38.50
2	Top bottom temperature (°C)	T_{min}	10.00	9.00	11.00
3	Optimum minimum temperature (°C)	T_{ob}	17.00	15.30	18.70
4	Optimum maximum temperature (°C)	T_{ou}	24.00	21.6	26.40
5	Radiation Use Efficiency (g MJ^{-1})	RUE	3.10	2.79	3.41
6	Extinction coefficient (--)	k	0.70	0.63	0.77

7	N concentration in the dry biomass at the end of the exponential growth period (g m^{-2})	a	6.66	5.99	7.33
8	Is the slope of the relationship (--)	b	-0.19	-0.21	-0.17
8	Slope of the curve (m^{-2})	c_1	3.08	2.77	3.39
10	Intersection coefficient (--)	c_2	175.64	158.08	193.20
11	Radiative coefficient (--)	A	0.24	0.22	0.26
12	Aerodynamic coefficient during day (W m^{-2} kPa^{-1})	Bd	37.60	33.84	41.36
13	Aerodynamic coefficient during night (W m^{-2} kPa^{-1}	Bn	26	23.40	28.60

Step 3. Calculation of the model outputs for each scenario. Using 10000 scenarios generated in step 2, the simulation was performed with the HortSyst model, the input variables (Figures 2-4) along with the sampling values of the thirteen parameters were used to calculate the predictions of the model.

Step 4. Distribution analysis of output variables. The minimum value, maximum value, mean value, variation coefficient (CV), skewness, and kurtosis statistics were calculated, as well as the histograms and the curves of the outputs for PTI, LAI, DMP, Nup and ETc predicted by the HortSyst model.

4.2.4 The Generalized Likelihood Uncertainty Estimation (GLUE) Uncertainty method

Regarding Bayesian methods, the Generalized Likelihood Uncertainty Estimation (GLUE) technique is an innovative uncertainty procedure (Beven and Binley, 1992, 2014; Beven and Freer, 2001; Makowski et al., 2002; Stedinger et al., 2008) used with environmental simulation models. GLUE popularity can be attributed to its simplicity and its applicability to nonlinear systems. This method is based on Monte Carlo simulation, in which parameter sets may be sampled from some probability distribution function (PDF). The most used PDF is a uniform distribution. Each parameter set is used to produce a model output; the acceptability of each model run is then assessed using a goodness-of-fit criterion which compares the predicted to observed values over some calibration period. Several likelihood functions can be used such as RMSE, the inverse error variance, efficiency index, etc. As part of the GLUE procedure. GLUE can be used both as a kind of calibration method or as an uncertainty propagation method. It is based on the concept of equifinality and can be seen as a method having similarities in approach with three of the above fourteen methods: Inverse modeling (parameter estimation), Monte Carlo analysis and multiple model simulations (Refsgaard et al., 2007). To evaluate the performance of the HortSyst model with this approach were run 2000 simulations using 10% and 20% of the variation of the nominal values of the thirteen parameters, with RUE of 3.1 (Jones et al., 1991) for season autumn-winter using Latin Hypercube Sample (LHS). To carry out the simulation of uncertainty analysis was used a Matlab toolbox for the application of global sensitivity analysis, called SAFE (Sensitivity Analysis for Everybody) that also is used for uncertainty analysis, the toolbox offers a number of visual tools including scatterplot, this toolbox is freely available from the authors for non-commercial research and educational uses (Pianosi, Sarrazin, & Wagener, 2015).

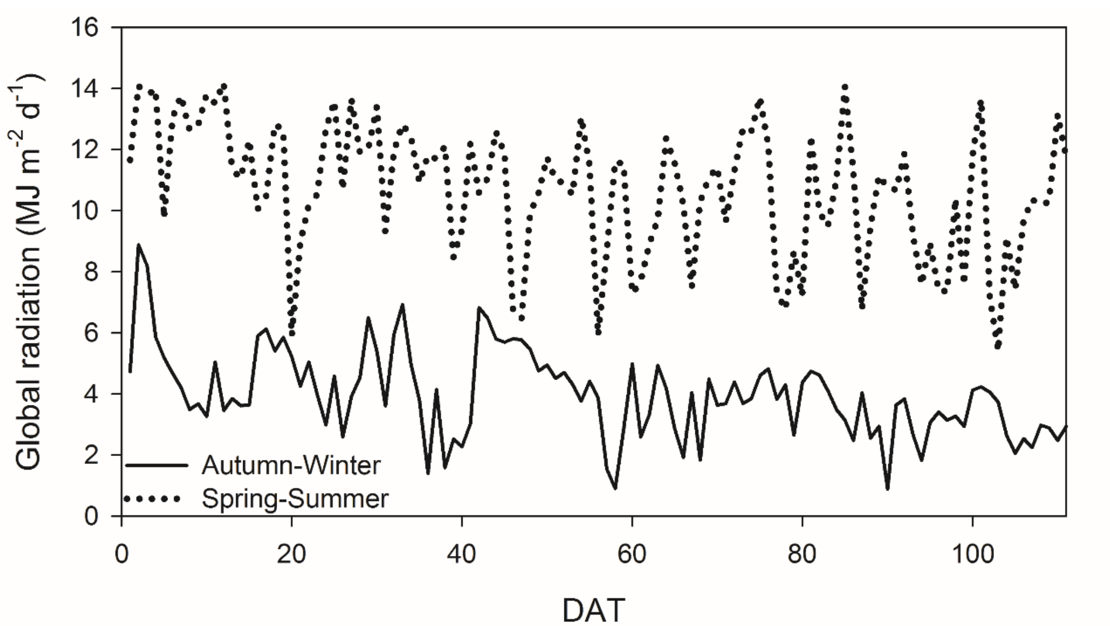

Figure 4.2 Daily averaged values of the global radiation measured inside of the greenhouses located in Chapingo, Mexico during autumn-winter, 2015, and spring-summer, 2016.

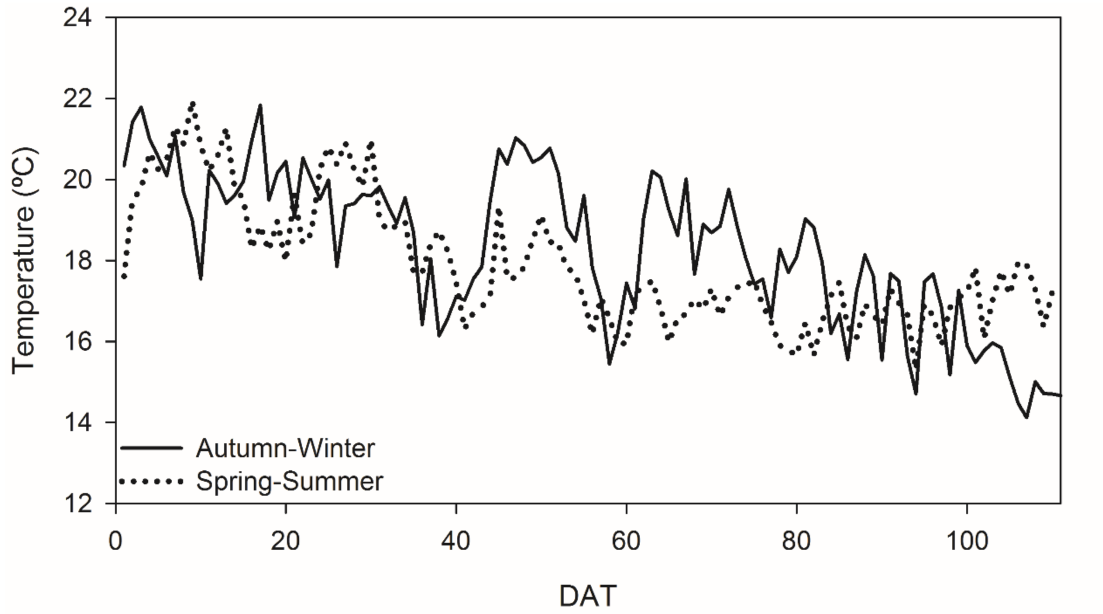

Figure 4.3 Daily averaged values of the air temperature measured inside of the greenhouses, located in Chapingo, Mexico, during autumn-winter, 2015, and spring-summer, 2016.

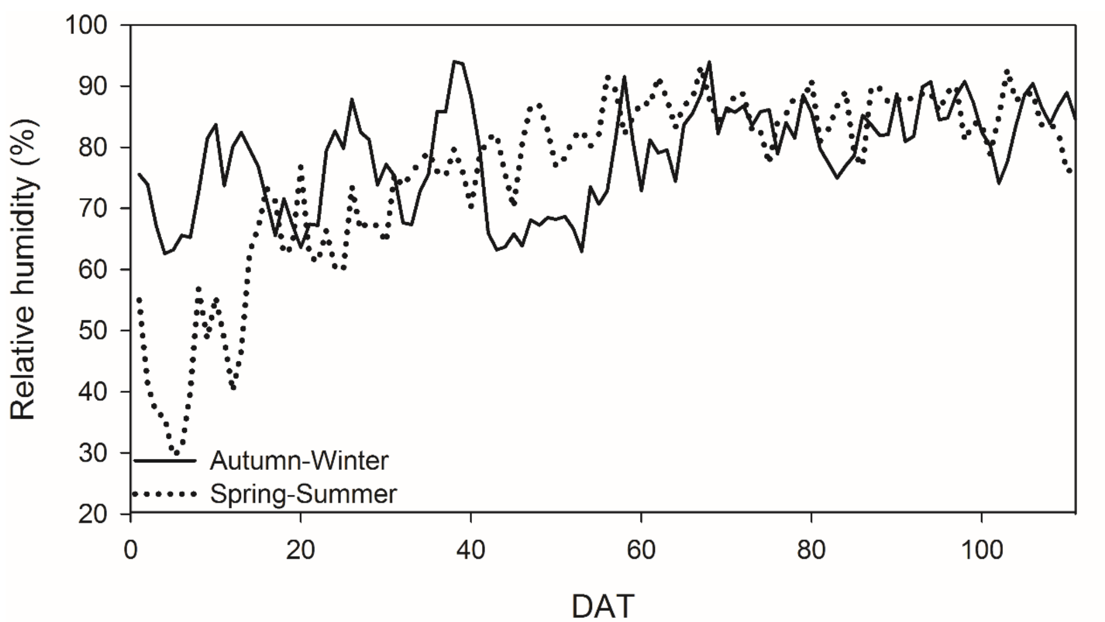

Figure 4.4 Daily averaged values of the relative Humidity measured inside of the greenhouses located in Chapingo, Mexico, during autumn-winter, 2015, and Spring-Summer, 2016.

4.3 Results

4.3.1 Model Output Uncertainty with Monte Carlo method

The HortSyst model predictions coming from 10,000 scenarios of simulation with 10% of the variation of the parameter values using LHS are shown for PTI in Figure 5a) and for LAI in Figure 5c). The measured values are included only in case of LAI variable because PTI values are computed during the simulations. The corresponding histograms of both variables (Figure 5b and Figure 5d) were also calculated using the total number of 10,000 simulations. These results were obtained using the input variables (global solar radiation, temperature and relative humidity) over the spring-summer cultivation period.

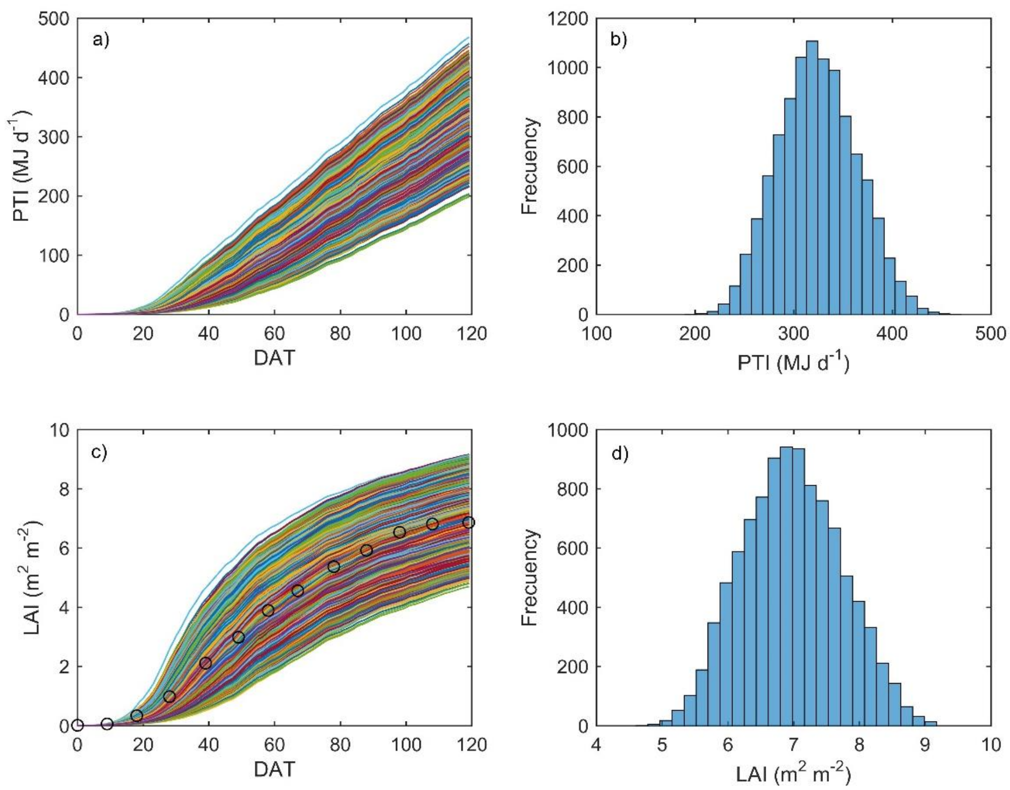

Figure 4.5 Output variables predictions by applying the tomato growth model HortSyst. a) and c) output simulation curves produced by the model for PTI and LAI, b) and d) histogram corresponding to PTI and LAI with 10% of parameters variation using LHS during the season spring-summer.

The DMP and Nup predicted by HortSyst model are shown in Figure 6a) and 6c) coming from 10,000 scenarios of simulation of variation of the parameter values using LHS. The measured values of both variables are plotted for reference. The corresponding histograms of both variables were also calculated and they are showed in Figure 6b) and 6d) over the spring-summer cultivation period.

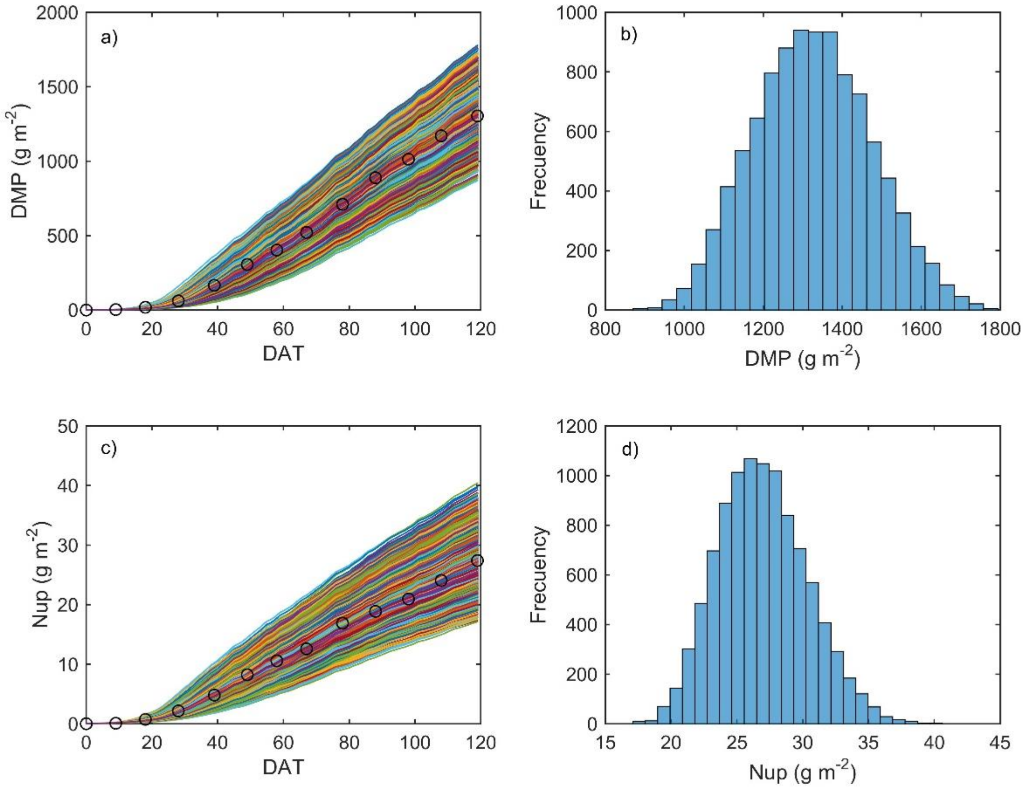

Figure 4.6 Output variables predictions by applying the tomato growth model HortSyst, a) and c) output simulation curves produced by the model for DMP and Nup, b) and d) histogram corresponding to DMP and Nup, with 10% of parameters variation using LHS during the season spring-summer.

The HortSyst model predictions corresponding to crop transpiration from 10,000 scenarios of parameter values using LHS are shown in Figure 7a). The measured values are plotted for reference as well. The corresponding histogram (Figure 7b) was also calculated using the total number of simulations (10,000). These results were obtained using the input variables over the spring-summer season.

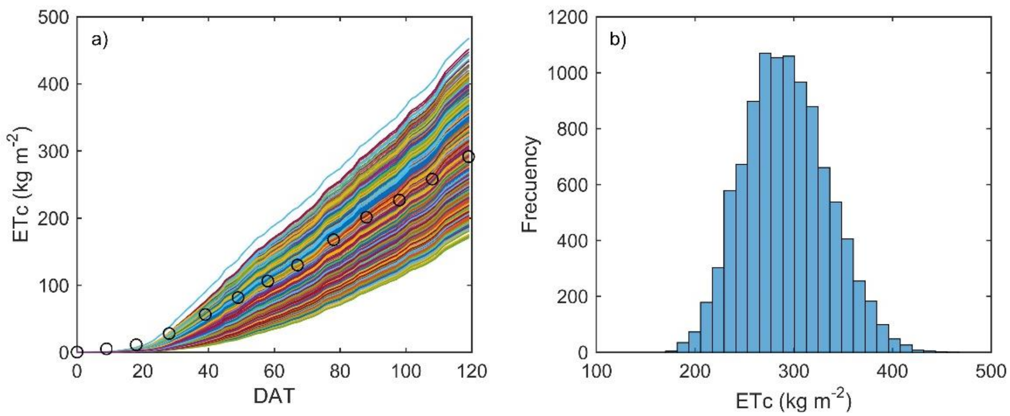

Figure 4.7 Output variables resulted from applying the tomato growth model HortSyst, for the crop transpiration (ETc); a) output v simulation curve produced, b) histogram corresponding to ETc respectively, with 10% of parameters variation using LHS sampling during the spring-summer season.

The output uncertainties were quantified by using the statistics; minimum value, maximum value, mean value, variation coefficient (CV), skewness and kurtosis as a result of the simulation with a Monte Carlo method. These statistical values using LHS are summarized in Table 3. The values of model parameters were varied by 10% and 20% around their nominal values; in general, the uncertainty of the model predictions was increased with a shorter uncertainty intervals as expected. The CV values of all variables were greater in the case of 20% than 10% of the uncertainty variation. For all the predicted variables the CV was lesser than 15% which means that the model is highly reliable. These were reflected in a change of the reduction of average values for all output variables of the model. Those predicted values were compared with the measured data at the end of the season of 6.86 m^2 m^{-2} for LAI, 1304 g m^{-2} for DMP, 27.4 g m^{-2} for Nup and 291.69 kg m^{-2} for ETc, the errors were -1.7%, -1.7%, 1.6% and -0.3%, respectively, this mean that the average values of LAI and DMP predicted were slightly over-estimated and the Nup were under estimated respect the observed data, the predicted average values of ETc was close to the measured these results were when the parameters were varied 10% around their nominal values. When the parameters were varied 20%, the errors were for LAI (0.1%), DMP (0.7%), Nup (3.2%) and ETc (1.5%) all the average values predicted by the model were under estimated compared with the measured data, the average values of LAI and DMP were closer to the measured values, the error of Nup average value moved away twice with the variation of the parameters from 10% to 20%, in case of ETc the average value were more underestimated when the uncertainty were increased to the 20%.The differences between maximum and minimum values were for PTI, 262.6 MJ m^{-2}, LAI, 4.73 m^2 m^{-2}, DMP, 1006.34 g m^{-2}, Nup, 23.65 g m^{-2} ,and ETc, 301.07 kg m^{-2} for 10% variation of the parameters and 492.9 MJ m^{-2}, 10.22 m^2 m^{-2}, 1900.3 g m^{-2}, 50.7 g m^{-2} and 607.2 kg m^{-2} , respectively, for 20% of variation, this show that the intervals of the predicted values increased more than twice with the varying of 20%. The uncertainty of the model predictions increases accordingly to the increase of uncertainty generated in the parameters around their nominal values. It is observed in the large difference values of all the predicted variables using 20% of parameters' variation respect to 10%.

Table 4.3. Statistics calculated for variables predicted by the HortSyst model at the end of the cultivation period, using 10000 samples with variation of 10% and 20% of the nominal value of the parameters obtained by Latin Hypercube sampling of thirteen model´s parameters using a uniform probability function.

Statistics	PTI		LAI		DMP		Nup		ETc	
	10%	**20%**	**10%**	**20%**	**10%**	**20%**	**10%**	**20%**	**10%**	**20%**
Minimum	190.34	69.19	4.52	1.93	778.74	332.58	16.95	8.24	154.88	52.01
Maximum	453.15	562.16	9.25	12.15	1785.08	2232.96	40.60	58.94	455.95	659.22
Mean	324.29	314.35	6.98	6.85	1326.04	1294.34	26.97	26.53	292.44	287.26
Variation coefficient	12.28	25.05	10.67	22.11	11.09	23.01	12.78	25.99	14.47	29.47
Skewness	0.10	0.18	0.08	0.18	0.11	0.19	0.28	0.61	0.21	0.46
Kurtosis	2.70	2.65	2.61	2.66	2.64	2.65	2.83	3.39	2.80	3.11

The skewness values were positive for all the variables which means that data are more spread out to the right of the distribution, which is observed in corresponding histograms (Figure 5b, Figure 5d, Figure 6b, Figure 6d, Figure 7b and Figure 7d). All the skewness values are very close to zero, which means that the distributions are similar to a normal distribution. The last observation is consistent with the Kurtosis values calculated for all the model outputs, which turned out to be closed to 3.0 that is the expected value of a normal distribution.

4.3.2 Model Output Uncertainty with GLUE method

The output uncertainties for PTI, LAI, DMP, Nup, and ETc were computed by the 95% confidence interval using the generalized likelihood uncertainty estimation (GLUE) Method of their accumulative distributions using 2000 simulations using uniform probability distributions and LHS and the RMSE as a likelihood function. Figures (8 and 9) show the simulated with 95% confidence interval limits around the value average. That is approximated as the difference between 2.5th and 97.5th percentile under the cumulative distribution curve of the output for 10% and 20% of the parameter variation respectively. In addition the measured values of LAI, DMP, Nup, and ETc were included during the analysis. With 10% variation of the parameters, it was found less uncertainty for all output variables (Figure 8). However, to use the model to make predictions it is not enough varying 10% of the parameter values. It is advisable to analyze the outputs by varying 20% to be able to rely on the predictions of the model (Figure 9). From the simulation of the model with GLUE method, also were obtained the scatterplot of the parameters affecting on the output variables (Figure 10-12). As it was mentioned, this procedure could give an estimation of the value of the parameters calibrated, which minimized the error between simulated and measured data (RMSE). Best values for RUE parameter were between 4.0 – 5.5 MJ m^{-2} (Figure 6). The scatterplot for LAI parameters the best values of parameter c_1 (2.5 - 3.3 m^2) and c_2 (60 – 85) were shown in Figure 11a and Figure 11b. Meanwhile, Figure 11c and Figure 11d show the parameters for Nup; a (6.0 – 7.5), b (-0.2 – 0.15). Nevertheless, the ETc simulations could not find a clear pattern of its calibrated parameter associated with small RMSE values. Besides, of the scatterplot of the parameters of each outputs, the Figure 12 (a, b, c d) show the planting density (d) associated with each of outputs, and clearly the good performance of the model was found between 3 - 4 plants m^{-2} of crop density specifically for LAI and ETc. So plant density played an important role in the performance of the model it had major effect on LAI and ETc. With a density higher that 3 plants m^{-2} it was observed better performance for Nup and

DMP, according to Figure (12) with density less to 3 plants m^{-2} the model could not have good performance.

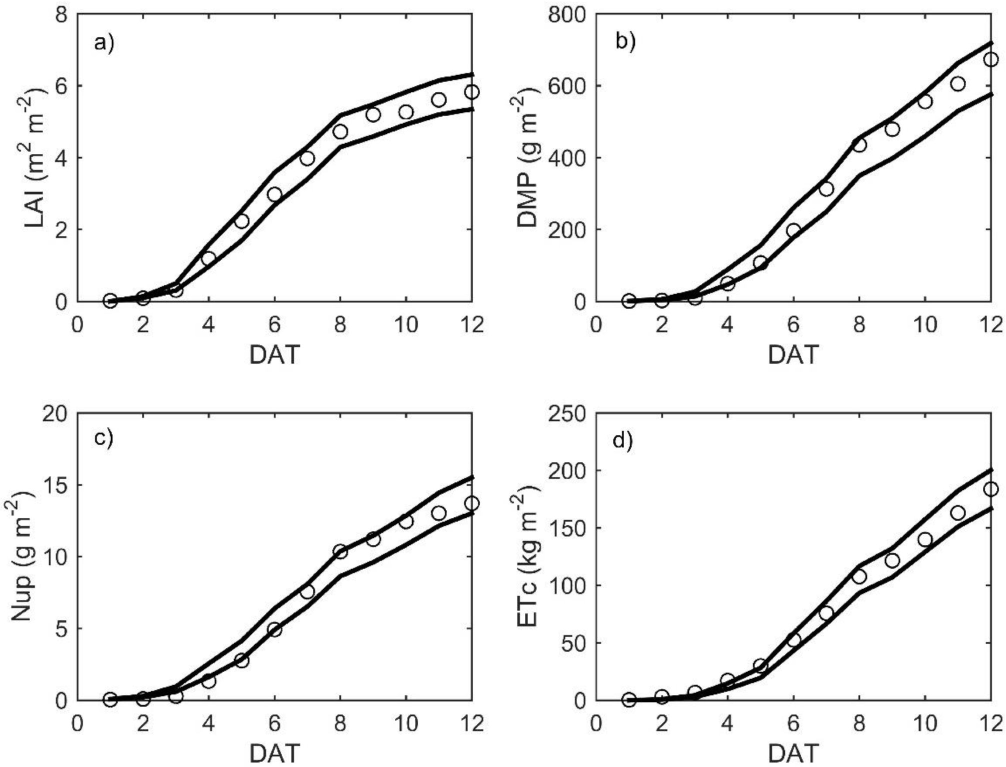

Figure 4.8 Simulation (2000) of the LAI (a), DMP (b), Nup (c) and ETc (d) obtained by HortSyst model by using the GLUE method with 95% of confidence interval with 10% of variation of the parameters, using LHS during the season autumn-winter.

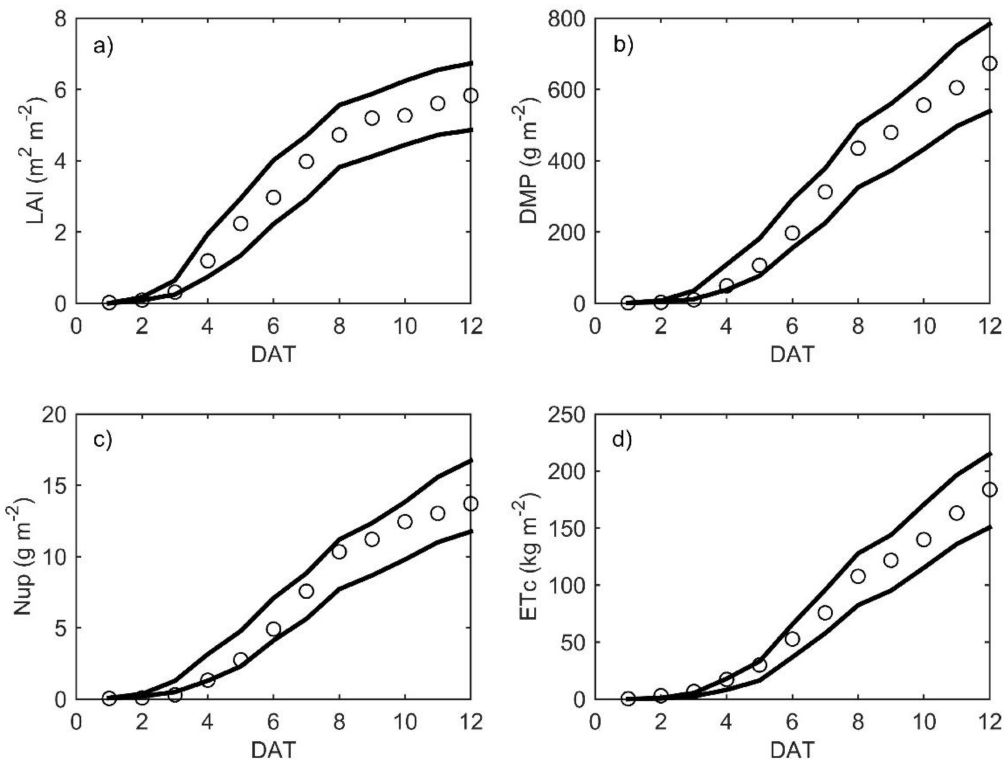

Figure 4.9 Simulation (2000) of the LAI (a), DMP (b), Nup (c) and ETc (d) obtained by HortSyst model by using the GLUE method with 95% of confidence interval with 20% of variation of the parameters, using LHS during the season autumn-winter.

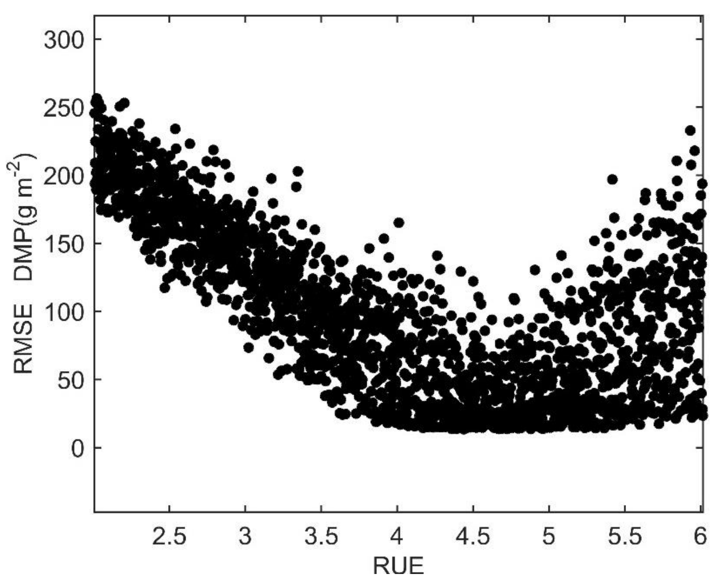

Figure 4.10 The scatter plot of the parameter RUE respects RMSE of DMP variable with 2000 simulations.

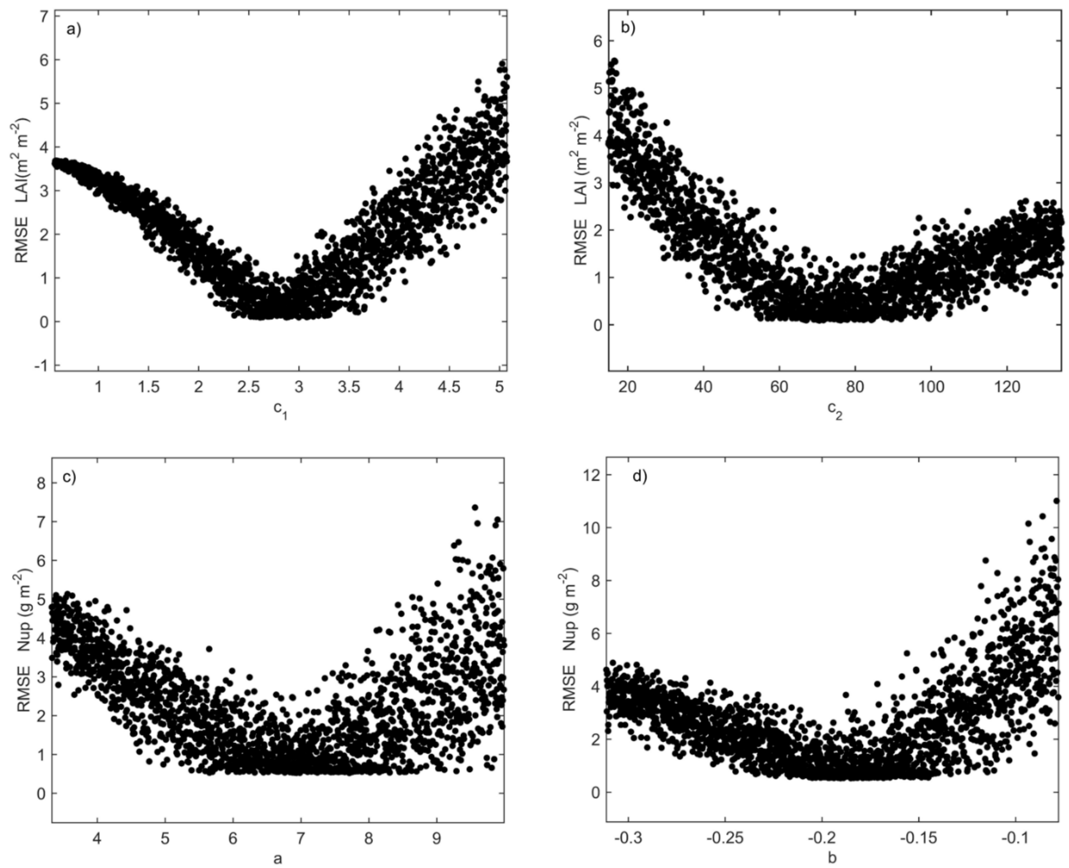

Figure 4.11 Scatter plots of the parameter c1, c2 respect RMSE of LAI and a, b respect RMSE of Nup variable with 2000 simulations.

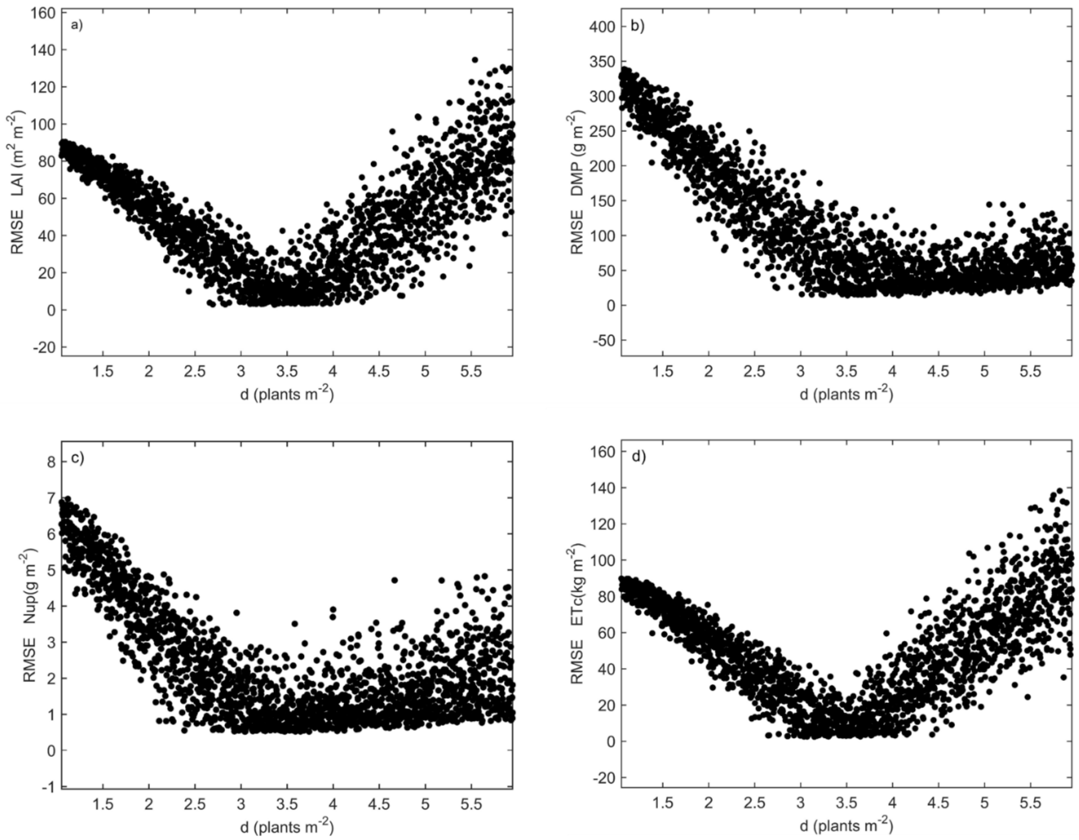

Figure 4.12 Scatter plots of the parameter d respect RMSE of LAI, DMP, Nup, ETc variable with 2000 simulations.

4.4 Discussion

In the simulation with 10% of uncertainty in the model parameters, the greatest variability using the coefficient of variation (CV) were for the ETc (14.47%), followed by Nup (12.78%), PTI (12.28%), DMP (11.09%), and LAI (10.67%) with the lowest variability. A similar performance was observed by 20% of variation of the parameters where the corresponding CV values were for ETc (29.47%) > Nup (25.99%) > PTI (25.05%) > DMP (23.01%) >LAI (22.11%). The CV values for DMP were slightly higher than those reported by López et al. (2012) who evaluated the NICOLET model for lettuce in the greenhouse. However, these results were different and better than those reported for LINTUL and SUCROS 87 (Monod et al., 2006), where the values of these statistics were found about 70% and 150% for some variables predicted by those models and less than the range from 19% to 33% found by Dzotsi et al. (2013) for simple SALUS model.

Even considering the results that were obtained by variation of 20% of the parameters, the coefficients of variation in the values for each of output were still lesser than those reported by Pathak et al. (2012) who found the CV values for model predictions of LAI ranged between 47 and 56% and similarly for aboveground biomass component had values as high as 53%. In case of ETc variable Baroni and Tarantola (2014) found values relatively low of the uncertainty estimation with mean value in range of 280±45 mm, this was closer that the values found in this research.

According to the Kurtosis calculated for all the predicted outcomes, it resulted around to three (Table 3). Thus, the distributions of all the outputs had a normal distribution. This could be confirmed by Figure 5b, 5d, 6b, 6d, and 7b). The Skewness of all predictions of the model turned out to be positive but close to zero (Table 3) which means mean that the data were more spread out slightly to the right tail of the distribution were slightly longer. This behavior could be seen in the histograms (Figure 5b, 5d, 6b, 6d, and 7b). The distributions of all the variables were symmetric because the Skewness values were close to zero. This symmetry was also found by López et al. (2012) for total biomass of lettuce with the exception of N uptake that tend slightly to an asymmetric pattern, López et al. (2012) found greater asymmetry for nitrate content for NICOLET model.

Table 2 showed that when the nominal value of the parameters was varied from 20% to 10%, which mean decreasing the uncertainty that was incorporated into the model, the coefficient of variation (uncertainty) of the predicted PTI, LAI, DMP, Nup, and ETc was reduced roughly 50%. In both cases LAI and DMP were predicted more accurately than PTI, Nup, and ETc. Taking into account the error of the mean value of simulation against the measuring data for output variables, it was evident that the model had a good quality of prediction, even though the parameter values were varied to 20%.

The estimation of the model outputs uncertainty using GLUE procedure improved the model performance based on sets of the parameters. According to Pathak et al. (2012), this procedure and Monte Carlo method estimated the uncertainty under the assumption that the parameters were independent. It was important consider that the model output uncertainties depend only on the uncertainty associated with the model´s parameters. Other sources of uncertainty as mentioned by Gal et al. (2014) were not considered. However, Gal et al. (2014) agree that the unknown uncertainty of the model associated with the uncertainty of parameters under different climatic conditions (as a certain parameter could vary from one environmental condition to another) an uncertainty analysis on the model could be used to assure that the model uncertainty does not limit their effectiveness as a management tool, in order to reach the desired level of confidence in the results and often robust information for decision-making (Zhao et al., 2014).

4.5 Conclusions

The results obtained in this study indicate that the uncertainty analysis using Monte Carlo and the GLUE procedure, these methods can help us to quantify the uncertainties of the model predictions when the model intends to be applied for recommendations for the management of production systems. Because of the low uncertainty associated to the output variables, the HortSyst model is a reliable model that could be used for decision support system for management of the irrigation scheduling and nitrogen supply in greenhouse tomatoes under soilless culture. This has also demonstrated an efficient estimation of the uncertainty in the model outcomes by the widely accepted GLUE procedure. This methodology could be useful in the estimation of the uncertainty and could asses the suitability for purpose of model parameter estimation, and it allowed to estimate the amount of variability in model predictions with coupling of the measured data. For uncertainty analysis, it is not enough quantifying the uncertainty of the model only considering the uncertainty associated with the parameters, as it was mentioned there are many sources of uncertainty. We should consider other model uncertainty sources, to have a complete analysis and measure the correlation between parameter but this is another type of analysis which do not correspond to the objectives set in this research.

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5. UNCERTAINTY ANALYSIS OF MODIFIED VEGSYST MODEL APPLIED TO A SOILLESS CULTURE TOMATO CROP

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Abstract

Over the last decades, the soilless culture technique has rapidly progressed in several developed countries linked to crop growth control environment and automation. Several crop growth models have been developed for decision support systems. Thus it is important to quantify the uncertainty associated to the predicted variables of these models previously to their application. An uncertainty analysis aims to know quantitatively the variability of model components for a specific situation and the derivation of an uncertainty distribution for each state variable and model output. Recently, the VegSyst model was developed to assist the Nitrogen (N) supply and irrigation management for some horticultural crops. The basic input data are measurements of air temperature, relative humidity, and solar radiation which are climatic data that are commonly measured, by growers, in the greenhouse. The model was developed assuming non-limiting conditions of water and N use. The aim of this research was to modify the VegSyst model including a leaf area index (LAI) sub-model, in order to improve the prediction of dry matter production (DMP), and N uptake (Nup) for a soilless culture using plastic bags filled with "tezontle" (volcanic sand) as substrate. LAI was modeled using accumulated normalized thermal time and photosynthetically active radiation. An experiment with a tomato crop was carried out during the autumn-winter 2015 in a greenhouse located at University of Chapingo, Mexico. The collected data were used to carry out an uncertainty analysis in which the inputs were the model parameters and the outputs were the predicted DMP, LAI, and crop N

content. Probability Density Functions were defined for each model parameter to calculate the corresponding statistics and histograms of the model outputs. Also the Generalized Likelihood Uncertainty Estimation (GLUE) Bayesian method was used. Results showed that LAI can be predicted better by the model than DMP and Nup.

Keywords: Mineral nutrition, Simulation model, Decision Support System, Monte Carlo, Bayesian method

5.1 Introduction

Over the last decades, the soilless culture technique has rapidly progressed in several developed countries linked to control environment and automation. Several crop growth models have been developed for decision support systems, thus it is important to estimate the uncertainty associated to the predicted variables of these models previously to their application.

The identification and quantification of uncertainty is recognized as an essential component for both model development and application. In an uncertainty study, we need to know how much uncertainty there is in the model output and where the uncertainty comes from. Thus an uncertainty analysis focuses in quantifying the amount of uncertainty in the model output can be connected to different sources of uncertainty in the model inputs (Helton et al., 2005; Saltelli et al., 2004). More specifically, an uncertainty analysis aims to know quantitatively the variability of model components for a specific situation and the derivation of an uncertainty distribution for each state variable and model output (Monod et al., 2006; Wallach et al., 2014). Roughly, two methods for uncertainty analysis can be identified: frequentists and Bayesians. In the first case the main steps are: i) objectives specification, ii) definition of sources of uncertainty by using probability density functions, iii) computation of model outputs and iv) calculation of statistics (Wallach et al., 2014). Regarding Bayesian methods the Generalized Likelihood Uncertainty Estimation (GLUE) technique is an innovative uncertainty procedure (Makowski et al., 2002) used with environmental simulation models. GLUE popularity can be attributed to its simplicity and its applicability to nonlinear systems. This method is based upon Monte Carlo simulation, in which parameter sets may be sampled from some probability distribution function (PDF). The most used PDF is a uniform distribution. Each parameter set is used to produce a model output; the acceptability of each model run is then assessed using a goodness-of-fit criterion which compares the predicted to observed values over some calibration period. Several likelihood functions can be used such as RMSE, the inverse error variance, efficiency index, etc. as part of the GLUE procedure.

Recently, the VegSyst model was developed to assist the Nitrogen (N) supply and irrigation management of horticultural crops (Gallardo et al., 2014; Gallardo et al., 2016). One of the most useful practical features of this model is that it provides effective simulation of Dry Matter Production (DMP), Nitrogen Uptake (Nup), and Evapotranspiration (ETC) for greenhouse crops. This model has been calibrated and validated for several vegetable crops (muskmelon, pepper and tomatoes) grown in Mediterranean-type plastic greenhouse (Gallardo et al., 2011; Gallardo et al., 2016). The simplicity of the model and its good performance for crops with different planting dates makes it suitable for its incorporation into decision support systems. So far there is a lack of uncertainty analysis for this model. Thus, the aim of this research was to modify the VegSyst model including a new thermal time concept and a leaf area index (LAI) sub-model, in order to improve the prediction of DMP and, N uptake. A second objective was to carry out an uncertainty analysis of the modified VegSyst model.

5.2 Material and methods

5.2.1 Experimental setup

The experiments were carried out in a research facility, located at University of Chapingo, Mexico (20° 19’ N, 98° 53’ W, and 2240 m) during the 2015 autumn-winter season. The experiment was carried out in a glass greenhouse type chapel with dimensions of 8 x 8 m, oriented N-S. A tomato (Solanum lycopersicum L.) crop cultivar "CID F1" was grown in a hydroponic system. Plastic bags of 10 liters of capacity were used which were filled with substrate "tezontle" (volcanic sand) with a density of 3.5 plants m-2. Tomato seeds were sown on 18 July 2015 and tomato seedlings were transplanted on 21 August 2015. A weather station (Onset Computer Corporation) was installed inside of the greenhouse. Temperature and relative humidity were measured with a S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with a S-LIB-M003 sensor was located 3.5 m above the ground. Both sensors were connected to a datalogger U-30-NRC model, which recorded data every minute. All data were taken from the central rows of the greenhouse. Dry weigh, LAI, and N uptake were measured each ten days.

5.2.2 Modified VegSyst (mod-VegSyst) model description

The VegSyst model simulates crop biomass production, crop N uptake and crop evapotranspiration in greenhouse grown vegetable crops (Gallardo et al., 2014; Gallardo et al., 2011; Gimenez et al., 2013). The model inputs are daily climatic data of maximum and minimum temperature, relative humidity, and integral of solar radiation. The model assumes that crops have no water and nutrient limitations. The modified VegSyst model described in discrete time has the photo-thermal time (TPTTP, MJ m^{-2} d^{-1}), the dry matter (DMP, g m^{-2} d^{-1}) and the nitrogen uptake (Nup, g m^{-2} d^{-1}) as state variables and these same variables besides the crop Leaf Area Index (LAI, dimensionless) are output variables. The dynamic equations and main modifications are given as follows:

$$TPTTP(k+1) = TPTTP(k) + \Delta TPTTP \quad (1)$$

$$DMP(k+1) = DMP(k) + \Delta DMP \quad (2)$$

$$N_{up}(k+1) = N_{up}(k) + \Delta N_{up} \quad (3)$$

$$\Delta TPTTP = \left(\sum_{j=1}^{24} TT(j) \right) / 24 \times PAR(k) \quad (4)$$

In contrast to the cumulative thermal time (CTT) which was used in the VegSyst model (Gallardo et al., 2011) in mod-VegSyst the product of thermal time and photosynthetically active radiation (PAR) proposed was used (Dai et al., 2006; Xu et al., 2010). The thermal time (TT, °C) is defined as the ratio of the growth rate under conditions of actual and optimum temperature conditions:

$$TT = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases} \quad (5)$$

where T_a, $T_{\min}$, $T_{\max}$, T_{ob}, T_{ou} (°C) are the air, top lower, top upper, optimum minimum and optimum maximum, temperature for crop growth, respectively.

$$PAR(k) = fPAR \times R_g$$
(6)

where Rg (MJ m^{-2} d^{-1}) is the daily global radiation above the crop and $fPAR$ (parameter) is PAR fraction of R_g.

$$\Delta DMP = RUE \times f_{i-PAR} \times PAR(k) \quad (7)$$

where RUE (dimensionless) is the parameter radiation use efficiency parameter.

Another major difference between VegSyst and mod-VegSyst is the calculation of the fraction of daily intercepted PAR (f_{i-PAR}) by using the exponential function instead of very complex light interception functions (Gallardo et al., 2011; Gallardo et al., 2014)

$$f_{i-PAR} = 1 - \exp(-k \times LAI(k)) \quad (8)$$

where k is the extinction coefficient.

Daily Leaf Area Index was modeled in mod-VegSyst using the concept photo-thermal time (Dai et al., 2006; Xu et al., 2010). It is worthwhile to mention that LAI is not modelled in the VegSyst model (Gallardo et al., 2011).

$$LAI(k) = A_f \times d \quad (9)$$

where d is the density of planting in the greenhouse. To simulate foliar area index, the Gompertz growth curve was used (Winsor, 1932). The leaf area (A_f , m^{-2})

$$A_f = c_1 \times \exp(-\exp(c_2 - c_3 \times TPTTP(k))) \tag{10}$$

where c_1, c_2, c_3 are model parameters.

$$\Delta N_{up} = \frac{\%N(k)}{100} DMP(k) \tag{11}$$

The Nitrogen content is calculated by the following equation:

$$\%N(k) = a \times DMP^b(k) \tag{12}$$

where a and b are calibration parameters obtained from experimental data. The whole set of mod-VegSyst parameters are described in Table 5.1. The modified VegSyst model was programed in Matlab environment.

5.2.3 Uncertainty analysis (UA)

The influence of parameter uncertainty on model outputs uncertainty was studied through a series of forced perturbations on the parameters. An Uncertainty Analysis in dynamic models encompasses four main steps (Monod et al., 2006; Wallach et al., 2014). 1) Definition of objectives; which is our case was the assessment of model parameters uncertainties on outputs dry matter, nitrogen uptake and LAI. 2) Definition of sources of uncertainty which were the model parameter with uniform probability density functions. The 10% and 20% variation below and above the nominal values of the model parameters were used. 3) Generation of values of input factors and calculation of model outputs. Latin Hypercube sampling (Helton et al., 2005) was used to generate the model parameter values and Monte Carlo simulation was used to compute the model outputs. For both basic statistics and histograms calculations and GLUE analysis, 10,000 simulations were run. 4) Outputs uncertainty calculation. Several statistics and histograms were calculated from the Monte Carlo simulations. The last accumulated value of the predicted variables dry matter, nitrogen uptake and LAI by the model mod-VegSyst was used in the Uncertainty Analysis. Since the performed UA assumes that the model parameters are independent, a correlation analysis was not carried out. In case of GLUE the likelihood function was defined as the RMSE and 95% confidence intervals and scatter plots were calculated. The GLUE software which is programmed as part of the Sensitivity Analysis For Everybody (SAFE) Toolbox for Matlab (Pianosi et al., 2015) was used.

Table 5.1.Parameters of the modified VegSyst model with 20% of variation of their nominal value

Name	Definition	Nominal Value	Lower Bound	Upper Bound	Unit
Parameters					
Tmax	Top upper temperature	**35.00**	28.00	42.00	°C
Tmin	Top bottom temperature	**10.00**	8.00	12.00	°C
Tob	Optimum minimum temperature	**17.00**	13.60	20.40	°C
Tou	Optimum maximum temperature	**24.00**	19.20	28.80	°C
RUE	Radiation use efficiency	**4.01**	3.21	4.81	g MJ-1 PAR
a	N concentration in the dry biomass at the end of the exponential growth period	**12.38**	9.90	14.86	--
b	Is the slope of the relationship	**-0.07**	-0.06	-0.08	--
c1	Maximum foliar area	**1.79**	1.43	2.15	--
c2	Shape coefficient	**3.99**	3.19	4.79	--
c3	Shape coefficient	**0.03**	0.02	0.04	--
$fPAR$	Ratio converter Rg to PAR	**0.50**	0.40	0.60	--
k	Extinction coefficient	**0.70**	0.56	0.84	--
d	Plant density	**3.50**	2.80	4.20	Plant m-2
Outputs					
LAI	Leaf area index				--
DMP	Dry matter production				g m-2
N	Nitrogen uptake				g m-2

5.3 Resuts and discussion

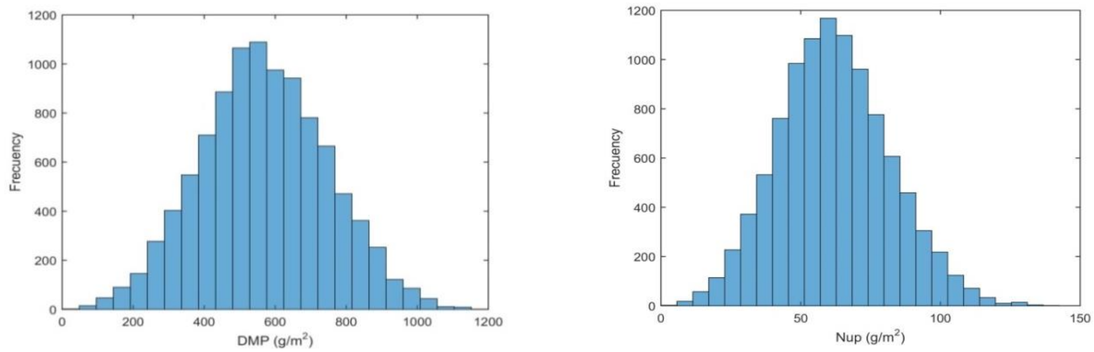

Figure 5 .1 Histograms corresponding to the DMP and Nup estimated at the end of the crop cycle, from 10000 samples of a uniform distribution for the mod-VegSyst model parameters using Latin hypercube sampling.

Figures 5.1 and 5.2 show histograms of the Dry matter production, Nitrogen uptake and Leaf area index predicted by the modified VegSyst model for Latin Hypercube sampling only in case of 20% of variation around the nominal values of the parameters. Table 5.2 shows main statistical measures.

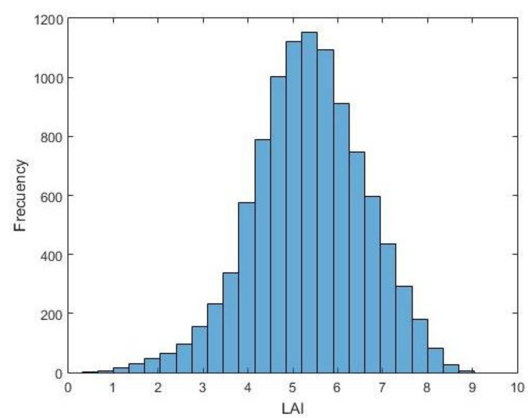

Figure 5.2 Histogram corresponding to the LAI, estimated at the end of the crop cycle, from 10000 samples of a uniform distribution for the modified VegSyst model parameters using Latin hypercube sampling.

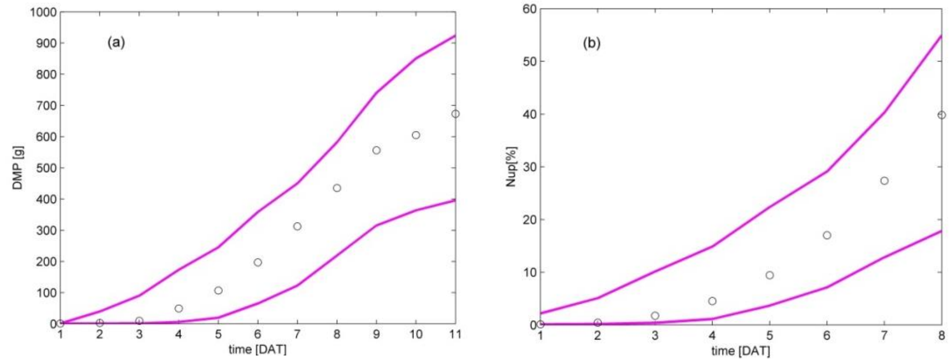

Figure 5.3 Figure 3. Simulation (10000) of the DMP (a) and Nup (b) obtained by modified VegSyst model by using GLUE method with 95% of confidence interval.

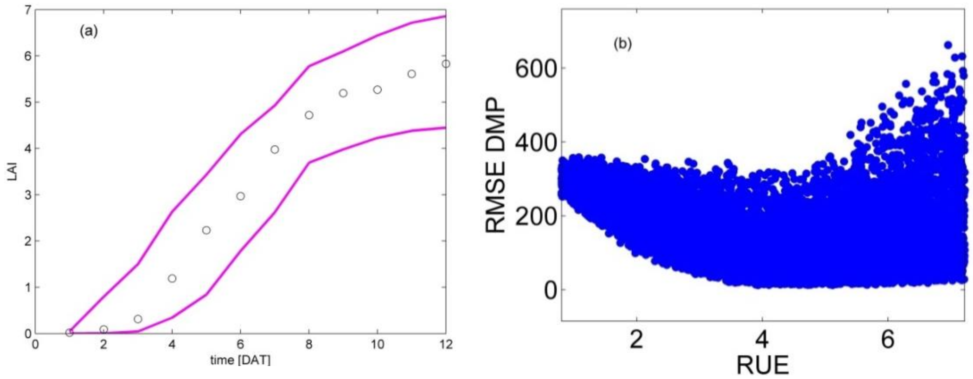

Figure 5.4 Simulation (10000) of the LAI (a) obtained by modified VegSyst model by using GLUE method with 95% of confidence interval and (b) the scatterplot of the parameter RUE respect RMSE of DMP variable.

The histogram of DMP turned out to be fairly symmetric as can be seen in Figure 5.1. This is confirmed quantitatively by its skewness value close to cero (Table 5.2). In contrast the histograms of Nup and LAI were less symmetric than the corresponding to DMP. They had larger skewness values. The negative value of skewness in case of LAI means that the data are more spread out to the left than to the right of the mean as it is confirmed by Figure 5.2. In case of DMP and Nup data are slightly, more spread out to the right than to the left of the mean. However, seemingly the three variables DMP, Nup and LAI follow a normal distribution given that their kurtosis values are close to 3.0 (Table 5.2).

Table 5.2.Statistics calculated for variables predicted by the mod-VegSyst model using 10000 samples with variation of 10% and 20% of the nominal value of the parameters obtained by Latin Hypercube sampling of thirteen model parameters using a uniform probability function.

Statistics	Dry Matter Production (DMP)		Nitrogen Uptake (Nup)		Leaf Area Index (LAI)	
	10%	20%	10%	20%	10%	20%
Minimun	294.22	22.81	33.50	2.72	3.53	0.31
Maximun	896.22	1189.97	100.33	141.81	7.30	8.82

Mean	588.54	568.36	64.09	61.90	5.63	5.35
Variation coefficient	15.25	31.42	15.67	32.48	10.19	23.26
Skewness	0.02	0.07	0.13	0.25	-0.05	-0.24
Kurtosis	2.77	2.80	2.87	2.98	2.83	3.21

Figures 5.3 and 5.4 show the 95% of confidence interval calculated by the GLUE method from 10,000 simulations for Dry matter production, Nitrogen uptake and Leaf area index for the model using the parameter's value by Latin Hypercube sampling of the model parameter values. The three variables are predicted quite precisely by the modified VegSyst model. Though, according to the coefficient of variation the LAI variable is better predicted by the model than DMP and Nup (Table 5.2). In fact, there is more uncertainty in the model regarding DMP and Nup than LAI predictions. Whether or not the mod-VegSyst model has similar or better performance than the original VegSyst model (Gallardo et al., 2011) requires a detailed comparison between the two models. Leaf Area Index can be modeled as a function of thermal time. This approach works well when daily temperature and radiation are closely correlated, but it is no longer valid for greenhouse or a winter crop as has been discussed by De Reffy et al (2009). We have proposed a better approach based on the photo-thermal concept (Xu et al., 2010). As it is seen in the figure 5.4b, RUE values has good performance when it takes value up to 3 which is according the remark made by De Reffy et al (2009) that a limitation of fraction of light intercepted occur when density is low, because the assumption of homogenous plantation densities.

Table 5.2 shows that when the nominal value of the parameters are varied from 20% to 10%, which means decreasing the uncertainty of the model parameters, the coefficient of variation (uncertainty) of the predicted variables DMP, Nup and LAI, are reduced almost 50% for the three output variable. However, as happening on increasing uncertainty, LAI is better predicted by the mod-VegSyst model than DMP and Nup.

5.4 Conclusions

The original VegSyst model was modified by replacing the original thermal time state variable by a photo-thermal time, namely the normalized thermal time times PAR as a state variable. A new and simpler light interception function which uses LAI was proposed. The uncertainty analysis based on Monte Carlo simulation and the GLUE approach shows that:

- The modified VegSyst model makes acceptable predictions of DMP, Nup and LAI.
- The LAI is predicted with slightly less uncertainty (more accurately) than DMP and Nup. The uncertainty associated with DMP and Nup is rather similar.
- The GLUE method can be very helpful in model calibration of greenhouse crops.

5.5 Reference

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6. GLOBAL SENSITIVITY ANALYSIS AND CALIBRATION USING A DIFFERENTIAL EVOLUTION ALGORITHM OF HORTSYST MODEL FOR TOMATO IN SOILLESS CULTURE

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Abstract

Simulation models of crop growth provide a widely accepted tool for assessing agricultural system management in response to weather and it is an important tool for growers to track crop development and improve for the management of irrigation with the aim to save water and nutrients and to reduce environmental impact. When the number of parameters increases in a model, the uncertainty of model predictions due to the uncertainty of parameters becomes more important. Under such conditions, it is important to determine the dominant parameters of the model. Sensitivity analysis is a first step to elucidate the importance of these parameters. Calibration of dynamic models is another issue of considerable interest which usually consist in adjusting the parameters to minimize the differences between model output variables and observed data. The aim of this work was carried out a global sensitivity analysis with Sobol's method for the HortSyst new nonlinear model to simulate the photo-thermal time, daily dry matter production, nitrogen uptake, leaf area index, crop transpiration, the model was calibrated with a differential evolution algorithm. Two experiments were set for autumn-winter and spring-summer with a tomato crop (*Solanum Lycopersicom* L) in soilless culture, with the sensitivity analysis nine parameters were selected to be calibrated, and the performance of the model after the calibration process showed an effectiveness fit the standard deviation of each parameter and the statistics of fit goodness found in the output responses were acceptable for both crop seasons.

Keywords: parameter estimation, irrigation management, crop nutrition, simulation model, uncertainty parameters.

6.1 Introduction

Tomato (*Solanum Lycopersicom* L) is one of the most important vegetable around the world and its cropping systems include the use of soil and hydroponics in which the nutrient solution and irrigation management is important to improve the nutrient uptake by plants. Simulation models of crop growth provide a widely accepted tool for assessing agricultural system management in response to weather and it is an important tool which may help growers to track crop development and improve the management of irrigation to save water and nutrients to reduce environmental impact. A number of vegetable crop models have been developed for simulating the dynamic responses of tomato to its environment (Gallardo et al., 2014; Heuvelink, 1999; Jones et al., 1991). A decision support system (DSS) based on a mathematical model requires a relatively simple simulation model to calculate the nitrogen uptake and daily crop transpiration using a small number of readily available data input. Various models are available that simulate nitrogen and water dynamics in the crop soil system such as EPIC (Williams et al., 1989) STICS (Brisson et al. 1998) and CropSyst (Stockle et al.,2003), but they are large and complex which require numerous input variables and generally have been developed for cereal crops. HortSyst is a new model that describes nonlinear dynamic systems and it simulates output variables such as photo-thermal index, dry matter production, leaf area index, nitrogen uptake, and crop transpiration. Therefore it is desirable to conduct a sensitivity analysis (SA) to determine which parameters requires more certainty. SA investigates the relation between parameters and outputs of a simulation model. In this context “parameters” are primarily equations coefficients and the threshold values in the model. An output is the value of any variable computed by the model or any feature or statistics extracted from it. The supposition is that each parameter and output can be described by a single number (Norton, 2015). Saltelli et al. (1995) define SA as “the study of how uncertainty in the output of a numerical model can be apportioned to different sources of uncertainty in the model input”. The aim of SA is to determine how sensitivity the output of a model is with respect to the elements of the model, which are subject to uncertainty or variability (Pianosi and Wagener, 2015); SA methods are typically classified as local (i.e, derivative based) or global (Saltelli et al., 2008). When the purpose of the SA is to study the effect of several input parameters on the model output responses, local SA is less useful than global sensitivity analysis (GSA), because the effect by second and higher sensitivity indices of the parameters interaction would be missed and the first order sensitivity inadequately represent model variation in change in input (Ogejo et al., 2010) where the output variability is evaluated while the input factor vary in their individual uncertainty domains (Monod et al., 2006). GSA methods such as, Morris (Morris,1991), Fourier Amplitude Sensitivity Test (FAST) (Saltelli et al., 1999) and Sobol’s method (Sobol 1993) can determine not only sensitivity of individual factor, but sensitivity of interactions between factors, as well very little SA literature exist for crop models that concentrate specifically on the methodology, particularly sensitivity differences between GSA methods. When the number of parameters increase, the uncertainty of model predictions due to the uncertainty of parameters becomes more important. Under such conditions, it is important to determine the dominant parameters of the model (Cooman and Schrevens 2006). Sensitivity analysis is a first step to elucidate the importance of these parameters (Cooman and Schrevens, 2007). Calibration of dynamic models is another issue of considerable interest which usually is done by adjusting the parameters to minimize the difference between simulated and observed data. Usually, the outputs are observed at specific sampling time, leading to a set of measurements (van Straten, 2008; Vazquez-Cruz et al., 2014). Recently, some research has applied global methods like evolutionary techniques as genetic algorithm and evolution strategies. Differential evolution algorithms are a population-based optimization methods that attacks the starting point problem by sampling the objective function at multiple, randomly chose initial point (Storn and Price, 1997). As evolutionary algorithms they also use operators to seek for the best solution after a number of generations and was designed to be a stochastic direct search method and it has good convergence properties. This is an optimization and heuristic search technique that use techniques inspired by evolutionary biology such as inheritance, mutation, selection and crossover (Price et al., 2005). Some works where this tool has been used were in the calibration of SUCROS model using evolutionary and bio-inspired algorithms for Husk tomato crop by César et al. (2014), the application of genetic algorithms for TOMSEED model (Katsoulas et al., 2015), and Dai et al. (2009) used a genetic algorithm for cucumber growth model. Prior to proper calibration of mathematical model, it is important to carry out a sensitivity analysis, which evaluate the relative importance of output variables and model parameters on the evolution over time of the state variable(Saltelli et al., 2000).

The aim of the current work was to perform a sensitivity analysis on HortSyst Model using the Sobol´s methods in order to select the most sensitive parameters of the model. Once the parameters with high sensitivity were selected it was carry out a calibration of the parameters using a differential evolution method.

6.2 Material and methods

6.2.1 Greenhouse condition and data acquisition

Two experiments were carried out under greenhouse conditions, during the autumn-winter, and spring-summer season, located at the University of Chapingo, Mexico. Geographicaly located: 19° 29’ NL, 98° 53 WL and 2240 m. Two tomatoes (*Solanum lycopersicom* L.) crop cultivar "CID F1" were grown in hydroponic systems using volcanic sand (Tuff) as a substrate. Plants were distributed with a density of 3.5 plants m^{-2}. For the first experiment, tomato seeds were sown on 18 July 2015, and the plants were transplanted on 21 August 2015, in a type chapel glasshouse with 8 x 8 m dimensions. The seeds for the second experiment were sown on 24 March 2016 and transplanted on 24 April 2016, in a plastic greenhouse with natural ventilation with dimensions of 8 x 15 m. Both experiments were fertilized with Steiner nutrient solution (Steiner, 1984). A HOBO weather station (Onset Computer Corporation) was installed inside of the greenhouses. Temperature and relative humidity were measured with an S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with an S-LIB-M003 sensor located at 3.5 m above the ground. Both sensors were connected to a data logger U-30-NRC model, and the data were recorded every minute, and subsequently the data were processed to obtain average data at hourly intervals.

In each experiment, three plants were chosen randomly for the sampling of each ten days to measure dry matter, nitrogen uptake, and leaf area index. The plants were dried out during 72 h at 70 °C in an oven. Nitrogen was determined by the Kjeldahl method. The leaf area index was estimated by a nondestructive method which consisted in taking four plants randomly in order to get measurements of width and length of the plant's leaves and also the total leaf area using a plant canopy analyzer LAI-3100 (LI-COR, USA). From the measurements, nonlinear regression models were fitted in order to estimate this variable, because the plants sampled during the measurement of the transpiration had to be kept alive until to end of the experimental phase. The crop transpiration was measured every minute by a weighing lysimeter located in a central row of the greenhouses. The device includes an electronic balance (scale capacity =120 kg, resolution ± 0.5 g) equipped with a tray carrying four plants for both experiments. The weight loss measured was assumed to be equal to the crop transpiration.

6.2.2 Model Description

The dynamic HortSyst model (Martinez et al., 2017) assumes that the crop have no water and nutrient limitations, and it simulates Photo-thermal time (PTI, MJ d^{-1}), dry matter production ($DMP,$ g m^{-2}), and Nitrogen uptake ($Nup,$ g m^{-2}) as the state variables the leaf area index ($LAI,$ m^2 m^{-2}) and crop transpiration (ET_c, kg m^{-2}) as output variables. In Table 1 are listed the mathematical equations of the three-state variables and the two output variables. Figure 1 shows the general structure of the model using a Forrester diagram. The model structure is based on VegSyst model developed by Gallardo et al. (2011), Gallardo et al. (2016), Gallardo et al. (2014), and Giménez et al. (2013). The input variables of the model are hourly measurements of air temperature (°C), relative humidity (%), and integration of solar radiation (Wm^{-2}) (the minimum, average and maximum daily values) which are shown in Table 3. The models use the light (radiation) use efficiency approach (Kang et al., 2008; Lemaire et al., 2008; De Reffye et al., 2009) which allows the calculation of daily dry matter production (ΔDMP) Eq. (8) as a function of the photosynthetically active radiation (PAR) Eq. (9), crop characteristics such as leaf area index (LAI) Eq. (10) and the radiation use efficiency parameter (RUE, g MJ^{-1}) as has been proposed by several researchers (Shibu et al., 2010; Soltani and Sinclair, 2012). The fraction of light intercepted (f_{i-PAR}) formalism relies upon the leaf area index (LAI), which is the total functioning leaf area for a unit surface area of ground covered by the plant population. The extinction coefficient (dimensionless k parameter) is related to leaf size and leaf orientation; this assumption is usually robust and tolerates some shift for reality. Leaf area index (LAI), is modelled as a function of Photo-thermal time (PTI) using the Michaelis-Menten equation and is multiplied by the density of planting d to obtain the leaf area index(LAI). For this purpose, it has calculated the normalized thermal time (TT, °C) with Eq. (6) and it is defined as the ratio of the growth rate under conditions of actual and optimum temperature conditions according to Dai et al. (2006).Then daily Photo-thermal time (ΔPTI) Eq. (5), is calculated as the product of normalized thermal time with the fraction of light intercepted(f_{i-PAR}) and PAR radiation, then the accumulation of PTI is calculated as Eq. (1) (Xu et al., 2010).

For daily nitrogen uptake ΔN_{up}, first the nitrogen content $\%N$ is calculated with the exponential model (Tei et al., 2002) eq. (11). And it is a function of the daily dry matter production (ΔDMP) and uptake nitrogen is simulated by Eq. (12). Then its accumulated value is given by eq. (3). Finally, the crop transpiration (ETc) is computed hourly, with Global radiation, vapor pressure deficit, the fraction of light intercepted and leaf area index as shown in eq. (14). And it is accumulated with equation (4).

Table 6.1 HortSyst model equations

Variable	Definition	Equation		Units
$\boldsymbol{PTI}$	Photo-thermal time	$PTI(j+1) = PTI(j) + \Delta PTI$	(1)	$MJ\ m^{-2}$
$\boldsymbol{DMP}$	Dry matter production	$DMP(j+1) = DMP(j) + \Delta DMP$	(2)	$g\ m^{-2}$
$\boldsymbol{N_{up}}$	Nitrogen Uptake	$N_{up}(j+1) = N_{up}(j) + \Delta N_{up}$	(3)	$g\ m^{-2}$
$\boldsymbol{ETc}$	Daily crop transpiration	$ETc(j+1) = ETc(j) + \Delta ETc$	(4)	$kg\ m^{-2}$
$\Delta\boldsymbol{PTI}$	Daily photo - thermal time	$\Delta PTI(j) = \left(\sum_{i=1}^{24} TT\,(i,j)\right) PAR(j) \times f_{i-PAR}(j)$	(5)	$MJ\ m^{-2}\ d^{-1}$
$\boldsymbol{TT}$	Normalized Thermal Time	$TT = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases}$	(6)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\boldsymbol{PAR}$	PAR	$PAR(j) = 0.5 \times R_g$	(7)	$MJ\ m^{-2}$
$\Delta\boldsymbol{DMP}$	Daily dry matter production	$\Delta DMP(j) = RUE \times f_{i-PAR}(j) \times PAR(j)$	(8)	$g\ m^{-2}$
$\boldsymbol{f_{i-PAR}}$	Intercepted PAR fraction	$f_{i-PAR} = 1 - \exp(-k \times LAI(j))$	(9)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\boldsymbol{LAI(j)}$	Leaf Area Index	$LAI(j) = \left[\frac{c_1 \times \Delta PTI(j)}{c_2 \times \Delta PTI(j)}\right] \times d$	(10)	$m^2\ m^{-2}$
$\%\boldsymbol{N(j)}$	Nitrogen content	$\%N(j) = a \times (\Delta DMP)^{-b}$	(11)	$\begin{bmatrix} dimension \\ less \end{bmatrix}$
$\Delta\boldsymbol{N_{up}}$	Daily Nitrogen Uptake	$N_{up}(j) = (\%N(j)/100) \times DMP(j)$	(12)	$g\ m^{-2}$
$\boldsymbol{ETc(i)}$	Hourly Transpiration	$ETc(i) = A \times (1 - \exp(-k \times LAI(j))) \times Rg(i) + LAI(DPV)B_{(d,n)}$	(13)	$kg\ m^{-2}\ h^{-1}$
$\boldsymbol{ETc(j)}$	Daily Evapotranspiration	$\Delta ETc = \sum_{i=1}^{24} ETc(i)$	(14)	$kg\ m^{-2}$

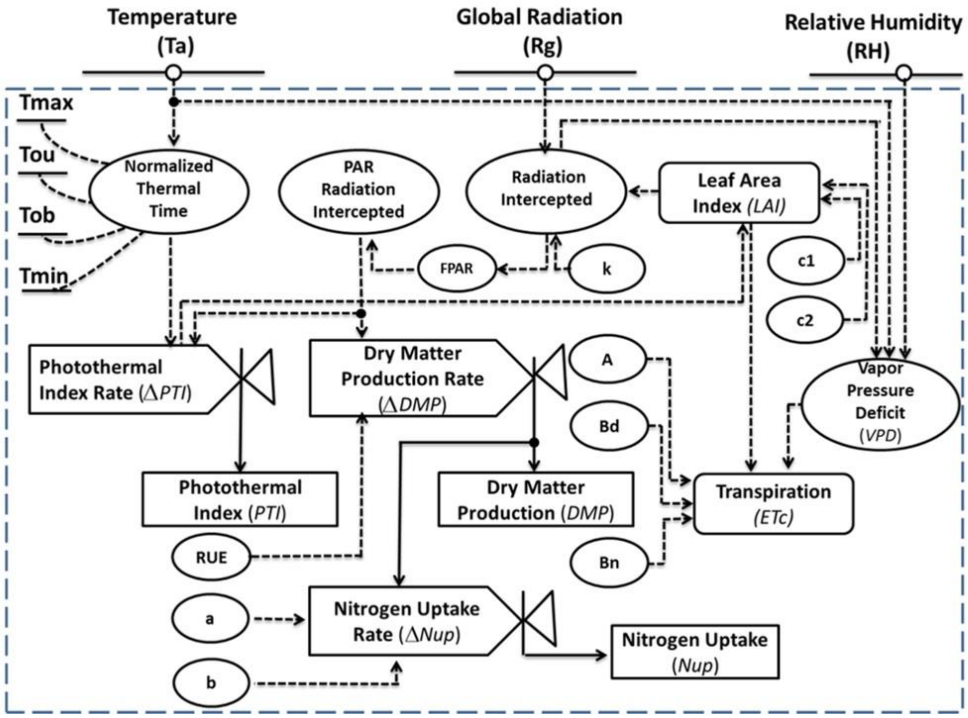

Figure 6 .1 Forrester diagram for the HortSyst crop Model with three state variables

6.2.3 Sensitivity analysis

In order to calculate the global sensitivity indices the following procedure proposed by Saltelli et al. (2008), Saltelli et al.(2000), and Saltelli et al. (2006) was applied.

Step 1. Objective specification. In order to determine which model parameter has a small or large influence on the state and outputs variables of the HortSyst model.

Step 2. Factor selection. Sixteen parameters of the HortSyst model were included in the sensitivity analysis and one set of parameter variation ranges were used, the upper and lower limits of the crop parameters, as is presented in Table. 2 it was determined by the 10% and 20% perturbation of the nominal parameters values taken from the literature for the spring and summer season crop.

Table 6.2 Definition of the HortSytst parameters used for simulation under experimental condition

No	Parameter	Symbol	Range 10%	Range 20%	Reference
1	Radiation Use Efficiency (g MJ^{-1})	RUE	2.79-3.41	2.48-3.72	Challa and Bakker (1998), Gallardo et al., (2014)
2	Extinction coefficient	k	0.58-0.70	0.51-0.77	Sánchez et al. (2011)
3	N concentration in the dry biomass at the end of the exponential growth period (g m^{-2})	a	6.79-8.31	6.04-9.06	Gallardo et al., (2014)
4	Is the slope of the relationship	b	-0.17-(-0.14)	-0.18-(0.12)	Gallardo et al., (2014)
5	Slope of the curve (m^{-2})	c_1	2.76-3.38	2.46-3.68	Estimated
6	Intersection coefficient	c_2	158.08-193.2	140.51-210.77	Estimated
7	Radiative coefficient	A	0.44-0.54	0.39-0.59	Sánchez et al. (2011)
8	Aerodynamic coefficient during day (W $m^{-}2$ kPa^{-1})	B_d	10.08-12.32	8.96-13.44	Sánchez et al. (2011)
9	Aerodynamic coefficient during night (W $m^{-}2$ kPa^{-1})	B_n	7.45-9.11	6.62-9.94	Sánchez et al. (2011)
10	Plant density (plants m^{-2})	d	3.15-3.85	2.8-4.2	stablished
11	Initial photo-thermal time (MJ m^{-2})	PTIini	0.06-0.07	0.05-0.07	Measured
12	Initial dry matter production (g m^{-2})	DMPIni	0.22-0.27	0.20-0.29	Measured
13	Top bottom temperature (°C)	T_{min}	9.00-11.00	8.00-12.00	Chu et al., (2009)
14	Top upper temperature (°C)	T_{max}	31.50-38.50	28.40-42.00	Chu et al., (2009)
15	Optimum minimum temperature (°C)	T_{ob}	15.30-18.70	13.60-19.80	Peet & Welles (2005)
16	Optimum maximum temperature (°C)	T_{ou}	21.60-26.40	19.80-28.40	Peet & Welles (2005)

Step 3. Choose the probability density function (PDFs). As no further information is available a uniform probability density was selected for each one of the parameters of the model.

Step 4. Selection of sensitivity analysis method. The Sobol's method were used which is based on the calculation of the variance (Monod et al., 2006; Saltelli et al., 2008) to obtain the main (first order) sensitivity indices and total sensitivity indices.

Step 5. Input sample generation. A sample of size (N=10000) was generated for Sobol's sampling method to achieve an adequate estimation of sensitivity analysis (Saltelli et al. 2008). The Latin hypercube sampling (LHS) was used for both methods because it is an efficient stratified sampling method according to (Helton et al., 2005).

Step 6. Model evaluation. Using the samples before mentioned the simulation was carried out to calculate the sensitivity for the parameters (Table 2) that are linked to the photo-thermal index (PTI), dry matter production (DMP), Nitrogen uptake (N_{up}), and crop transpiration (ETc). The temporal variation of parameters sensitivity indices was analyzed, in the days 10, 25, 40, 80 and 119 after transplant and also the sensitivity analysis was carried out integrating daily the outputs variables until the end of the experiment during the spring and summer.

Step 7. Analysis of the output model. The value of the sensitivity indices of first order and total sensitivity index (S_i and S_{Ti}) were estimated using Janon's estimator (Janon et al. 2014) to evaluate the importance of each of the HortSyst model parameters.

6.2.4 Global sensitivity analysis (GSA). Variance based method

The function $Y = f(\boldsymbol{X}) = f(X_1, X_2 \cdots X_k)$ is defined in the n-dimensional cube $\boldsymbol{K}^k$. If the input variables are mutuality independent, there exists a decomposition of $f(\boldsymbol{X})$ as in (Fang et al., 2015; Saltelli et al., 2010; Wu et al., 2012; Wu., 2014)

$$f(X_{1,\cdots,}X_k) = f_o + \sum_{i=1}^{k} f_i(X_i) + \sum_{1\le i<j\le k} f_{ij}(X_iX_j) + \cdots + f_{12\ldots k}(X_1, \ldots, X_k) \qquad (15)$$

Where $f_i = f_i(\boldsymbol{X_i}), f_{ij} = f(\boldsymbol{X_i}, \boldsymbol{X_j})$ and so on, this decomposition is called high-dimensional model representation from lower to higher order.

The basic idea of variance method is to decompose the function on interest into terms of increasing dimensionality as in Eq (1), such that all the summands are mutually orthogonal. The variance of the output variable Y can thus decompose into:

$$V(Y) = \sum_{i=1}^{k} V_i + \sum_{1\le i<j\le k} V_{ij} + \cdots + V_{1,2\ldots k} \qquad (16)$$

Where $V_i, V_{ij}, V_{1,2,\ldots,k}$ denote the variance of $f_i, f_{ij}, f_{1,2,\ldots,k}$ respectively. Where V is the variance operator and:

$$V_i = V[E(Y/X_i) \qquad (17)$$

$$V_{ij} = V[E(Y/X_i, X_j)] - V_i - V_j \qquad (18)$$

In this approach the first-order sensitivity index S_i, also called main effect index. For factor X_i, is given by

Dividing both sides of eq. (2) by $V(Y)$

$$1 = \sum_{i=1}^{k} S_i + \sum_{1\le i<j\le k} S_{ij} + \cdots + S_{1,2\ldots k} \qquad (19)$$

Where S_i is the first order sensitivity index

$$S_i = \frac{V[E(Y/X_i)]}{V(Y)} = \frac{V_i[E_{-i}(Y/X_i)]}{V} \qquad (20)$$

And S_{ij} denote the second order sensitivity index measuring the amount of output variance explained by interaction between X_i and X_j and so on.

$$S_{ij} = \frac{V[E(Y/X_i,X_j)] - V_i - V_j}{V(Y)} \qquad (21)$$

The total order index effect ST_i is introduced to account for the total contribution of the output variance due to X_i

$$S_{Ti} = S_i + \sum_{i<j\le k} S_{ij} + \cdots + S_{1,2\cdots k} \qquad (22)$$

It is hard to get ST_i by eq.(5) when many inputs are involved, and alternative way is,

$$S_{Ti} = 1 - \frac{V[E(Y/X_{-i})]}{V(Y)} = 1 - \frac{V_{-i}}{V(Y)} \tag{23}$$

Where $X_{-i} = (X_1, \cdots, X_{i-1}, X_{i+1}, \cdots, X_k)$ is the input vector without X_i

To obtain $V[E(Y/X_i)]$ and obtain $V[E(Y/\boldsymbol{X}_{-i})]$ one can use a set of Monte Carlo method to estimate the inner expectation, end then repeat the procedure many times for different obtain X_i or $(\boldsymbol{X}_{-i})$ to get the outer variance.

6.2.5 Sobol´s computing method

The standard Sobol´s method for SA was put forward in Sobol (2001), as one numerical simulation method to get the conditional expectation value for model output Y. We first decide the base sampling dimension N, and then we implement the following steps.

1. Generate a Monte Carlo sampling of dimension N of the input factor according to their random distributions and form the $N \times k$ matrix $U_{N\times k}$ (k being the dimensions of the input space) with each row a set of parameters; $N \times k$is called the “sampling matrix. “

$$U_{N\times k} = \begin{bmatrix} x_{1^{(1)}} & \cdots & x_{i^{(1)}} & \cdots & x_{k^{(1)}} \\ x_{1^{(2)}} & \cdots & x_{i^{(2)}} & \cdots & x_{k^{(2)}} \\ \vdots & & & \ddots & \vdots \\ x_{1^{(N)}} & \cdots & x_{i^{(N)}} & \cdots & x_{k^{(N)}} \end{bmatrix}$$

2. Generate another sampling matrix of dimension $N \times k$, $W_{N\times k}$ called the“ re-sampling matrix.”

$$W_{N\times k} = \begin{bmatrix} x_{1^{(N+1)}} & \cdots & x_{i^{(N+1)}} & \cdots & x_{k^{(N+1)}} \\ x_{1^{(N+2)}} & \cdots & x_{i^{(N+2)}} & \cdots & x_{k^{(N+2)}} \\ \vdots & & & \ddots & \vdots \\ x_{1^{(2N)}} & \cdots & x_{i^{(2N)}} & \cdots & x_{2k^{(N)}} \end{bmatrix}$$

3. Define a matrix $W'_{N\times k}$ formed by all columns of $W_{N\times k}$ except the ith column obtained from the ith column of $U_{N\times k}$

$$W'_{N\times k} = \begin{bmatrix} x_{1^{(N+1)}} & \cdots & x_{i^{(1)}} & \cdots & x_{k^{(N+1)}} \\ x_{1^{(N+2)}} & \cdots & x_{i^{(2)}} & \cdots & x_{k^{(N+2)}} \\ \vdots & & & \ddots & \vdots \\ x_{1^{(2N)}} & \cdots & x_{i^{(N)}} & \cdots & x_{2k^{(N)}} \end{bmatrix}$$

4. Define a matrix $U'_{N\times k}$ formed by all columns of $U_{N\times k}$ except the ith column obtained from the ith column of $W_{N\times k}$.

$$U'_{N\times k} = \begin{bmatrix} x_{1^{(1)}} & \cdots & x_{i^{(N+1)}} & \cdots & x_{k^{(1)}} \\ x_{1^{(2)}} & \cdots & x_{i^{(N+2)}} & \cdots & x_{k^{(2)}} \\ \vdots & & & \ddots & \vdots \\ x_{1^{(N)}} & \cdots & x_{i^{(2N)}} & \cdots & x_{k^{(N)}} \end{bmatrix}$$

5. Compute the model output for each set of input parameters from $N \times k$ and $W'_{N\times k}$ (that is to say for each row in $N \times k$ and $W'_{N\times k}$) to obtain two column vectors of model outputs of dimension N: $\boldsymbol{y} = f(U_{N\times k}), \boldsymbol{y}'_R = f(W'_{N\times k}), \boldsymbol{y}' = f(U'_{N\times k})$. Alternatively, Wu et al. (2012), argues that $\boldsymbol{y}'$ can also be used for $E_{-i}(Y/X_i)$ then the outer $V_i[E_{-i}(Y/X_i)]$ should be inferior because by doing the averaging, we will get more balanced simulation architecture.

6. The sensitivity indices are hence computed based on scalar products of the above defined vectors of model output.

The applicability of the sensitivity estimates S_i to a large class of functions $f(\boldsymbol{X})$ is linked to the possibility of evaluating the multidimensional integral associated with this estimates via Monte Carlo methods. For a given sampling size N tending to ∞ the following estimates for the mean value of the output is straight-forward.

$$\hat{f}_o = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)} + \boldsymbol{y}_R^{(j)}] \tag{24}$$

Where $\boldsymbol{y}^{(j)}$is the model output for a sample point in the parameter space $\boldsymbol{k}^{(k)}$ the gat symbol will be used to denote estimate.

To list the estimator for standard sobol's in Sobol (2001), the following notation will be introduced.

$$\bar{V} = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)^2} + \boldsymbol{y}_R^{(j)^2}] \tag{25}$$

$$\bar{V}_i = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)}\boldsymbol{y}'^{(j)}_R + \boldsymbol{y}_R^{(j)}\boldsymbol{y}'^{(j)}] \tag{26}$$

$$\bar{V}_{-i} = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)}\boldsymbol{y}'^{(j)} + \boldsymbol{y}_R^{(j)}\boldsymbol{y}_R'^{(j)}] \tag{27}$$

$$\bar{V} = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)} + \boldsymbol{y}_R^{(j)}]^2 \tag{28}$$

Then we estimate the output variance by

$$\hat{V} = \bar{V} - \hat{f}_o^2 \tag{29}$$

$$V_i[E_{-i}(Y/X_i)] \approx \hat{V}_i = \bar{V}_i - \hat{f}_o^2 \tag{30}$$

And finally

$$\hat{S}_i = \frac{\hat{V}_i}{\hat{V}} = \frac{\bar{V}_i - \hat{f}_o^2}{\hat{V}} \tag{31}$$

$$\hat{S}_{Ti} = 1 - \frac{\hat{V}_{-i}}{\hat{V}} = 1 = \frac{\bar{V}_{-i} - \hat{f}_o^2}{\hat{V}} \tag{32}$$

As mentioned in (Fang et al., 2015; Homma and Saltelli, 1996; Wu et al., 2012), to compensate the “systematic error” in standard Sobol’s method, better estimates for the term $V_i[E_{-i}(Y/X_i)]$ is obtained by also computing the output if the “re-sampling matrix ” $W_{N\times k}$ we denote it as $\boldsymbol{y}_R = f(W_{N\times k})$ we define γ^2.

$$\gamma^2 = \frac{1}{2N}\sum_{j=1}^{N}[\boldsymbol{y}^{(j)}\boldsymbol{y}_R^{(j)} + \boldsymbol{y}'^{(j)}\boldsymbol{y}_R'^{(j)}] \tag{33}$$

Then the variance estimator is chosen as

$$V_i[E_{-i}(Y/X_i)] \approx \hat{V}_i = \bar{V}_i - \gamma^2 \tag{34}$$

For the same reason

$$\hat{S}_i = \frac{\hat{V}_i}{\hat{V}} = \frac{\bar{V}_i - \gamma^2}{\hat{V}} \tag{35}$$

$$\hat{S}_{Ti} = 1 - \frac{\hat{V}_{-i}}{\hat{V}} = 1 = \frac{\bar{V}_{-i} - \gamma^2}{\hat{V}} \tag{36}$$

6.2.6 DE algorithm

Genetic algorithms (Gas) belong to a class of algorithms known as evolutionary computation. They imitate the process of natural evolution by assigning fitness values to possible solutions of the problem and applying a mathematical model of the Darwinian principle of survival of the fitness (Katsoulas et al., 2015). The DE algorithm is a population-based stochastic search technique that provides an effective methods of searching for the optimum solution to complex problems. In recent years, the DE algorithm has obtained increasing attention and has been widely used in scientific research. The DE algorithm mainly includes mutation, crossover operation and elimination mechanism. The significance of the scale factor, the crossover rate and the population size are three main control parameters of DE optimization algorithms. The calibration procedure of the HortSyst model was as follows: the DE algorithm generated the initial population of the parameters, using these values as the decision variables, the HortSyst model was run to simulate the output variables. The simulated values were then used to evaluate the fitness function, based on which the DE developed the next generation candidates. In the calibration process the fitness function is important to identifying the optimal values for the model parameters (Xuan et al. 2016).

6.2.7 Optimization problem description

Katsoulas et al. (2015) argue that each possible solution to the calibration problem consisted of a set of values for each of the parameters. In heuristic optimization, each solution must have a quality metric, usually referred to as "fitness" of the solution, which is estimated by an appropriate fitness function (César et al., 2014; Guzmán et al., 2009).The HortSyst crop model was calibrated by solving the minimization problem, which can closely match the simulated and observed data of the tomato crop. An objective function (fitness function) is commonly expressed as follows.

$$\hat{p} = \arg\min J\,(p) \tag{37}$$

$$J(p) = \sum_{h=1}^{L}\sum_{i=1}^{M} w_h\left[\bar{y}_h(t_i, p) - y_h(t_i)\right]^2 \tag{38}$$

$\bar{y}_h(t_i, p)$ is the simulated output y_h in time t_i , $y_h(t_i)$ is the measurement of the output $y_h(t_i)$ in time t_i, L is the number of outputs (L= 4), M is the number of samples during the growing period, Where w_h is the relative weight of each output variables; DMP, Nup, LAI and ETc (0.01, 10, 100,1) respectively. p is the parameters set of calibration and $\hat{p}$ is the parameter that reduces $J(p)$ to a minimum.

The performance of the models was evaluated using the BIAS and the RMSE, and EF statistics was defined as follows (Wallach et al., 2014):

$$BIAS = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right) \tag{39}$$

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2} \tag{40}$$

$$EF = 1 - \frac{\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{N}\left(Y_i - \overline{Y}_i\right)^2} \tag{41}$$

Where the number of measurements is N, $Y_{\boldsymbol{i}}$ is the measured value for situation i and $\bar{Y}_i$ is the corresponding value predicted by the model.

6.3 Resuts and discussion

The environmental conditions measured inside of the greenhouses were the air temperature, relative humidity and global solar radiation for the season autumn-winter and spring-summer, the minimum, mean and maximum values of these climatic variables are shown in Table 3.

Table 6.3 Values of global solar radiation (Rg), air temperature (Ta) and relative humidity (RH) during the two crop seasons.

Climatic variable	Autumn-Winter season			Spring-Summer season		
	Minimum	Mean	Maximun	Minimum	Mean	Maximun
$\boldsymbol{R_g}$ (MJ m^{-2})	0.88	3.99	8.89	5.40	10.59	14.18
$\boldsymbol{T_a}$ (^{o}C)	14.12	18.31	21.83	15.31	17.84	21.94
$\boldsymbol{RH}$ (%)	62.59	78.58	93.98	29.47	76.82	93.16

6.3.1 Sobol's method sensitivity analysis

The global sensitivity analysis with Sobol's method was carried out to select the parameters that are more sensitive to the uncertainty applied to all parameters defined as a variation of 10% and 20% around their nominal values, for this purpose the data of the climatic variables of spring-summer were used. The sensitivity indices estimated by Sobol's method are shown in Figure (2 and 3) for 10 % of the uncertainty of the parameters, the sensitivity analysis was run 10000 times at the start of fructification (40 DAT) and at the end of the crop cycle (119 DAT) for the HortSyst model. The parameters with more influence in the model are listed in Table 4. The sum of the first order (main effect) for PTI was (0.95) and the sum of total indices was 1.01; for DMP (1.00 and 1.00); for Nup (1.08 and 0.99); for LAI (1.01 and 1.00) and for ETc were (0.98 and 1.00) respectively. At the end of crop growth (111 DAT) the sum of the first order for PTI was 0.96; DMP = 0.92; Nup = 0.99; LAI = 1.04, and for ETc = 0.93, and total sensitivity indices for PTI was 1.00; DMP = 1.02; Nup = 1.01; LAI = 0.99, and for ETc = 1.00 in the fructification stage was not clear the existence of interaction between parameters, but for the second stage the values $S_{Ti} > S_i$.

In Figure (4 and 5) are shown the indices for 20% of uncertainty of the parameters for 10000 simulations at the start of the fructification and at the end of growth, in both cases the most important parameters were the same with uncertainty of 10% of the parameters, which varied in order of importance; these changes were most evident for 40 DAT, the most important parameters in descending order are shown in Table 4. When the fructification began the sum of the first order effects and the total indices were for PTI (1.08, 1.04); DMP (1.08, 1.04); Nup (0.99, 1.05); LAI (1.02, 1.05) and ETc (1.00, 1.06). The analysis in the day 119 after growth with 20% of uncertainty, the parameter d (crop density) became more important than c_1 for ETc output, the other parameters kept their order of importance as when 10% of uncertainty was applied. In case of 119 DAT the sum of the first order effects and the total indices were for PTI (0.90, 1.00); DMP (0.91, 1.01); Nup (0.95, 1.02); LAI (0.99, 1.00), and ETc (0.96, 1.02). When the sensitivity analysis was carried out with an uncertainty of 10% at 40 DAT and 111 DAT the sum of total sensitivity indices for the most important parameters ($\sum S_{Ti}$) was slightly higher than 1 but was not conclusive to say that the model is non-additive. Nevertheless, with the 20% of uncertainty, the sum of total indices for all output response for both stages of crop were different of 1, so the model was non additive, this also was checked with the sum of the first order effects S_i <1 according to Saltelli et al. (2008).

When the uncertainty of the parameters was increased to 20% the interaction between parameters was clearer because of all output variables $S_{Ti} > S_i$, either for the beginning of the fructification or at the end of the crop cycle. The sensitivity indices also were estimated taking into account the daily integration of each outputs variables until the end of crop cycle with 20% of uncertainty, the results were different in the values of the indices of some parameters (Figure 6) in comparison when two specific stages were considered in the analysis, in this analysis some parameters changed their influential for example, for PTI and DMP, T_{ob} and RUE decreased their indices values and the rest of the parameters increased, the parameter c_2 increased the magnitude of its indices for Nup, LAI and ETc. In the sensitivity analysis run in the two-stages of growth was observed that at the beginning of the fructification a greater number of parameters were more important than at the end of the crop growth for 10% and 20% of variation of the parameters (Table 4), these indicated that the parameters changed over time (Figure 7,8,9), some of them increased in importance and other decreased, for example the parameters T_{ob} increased its importance in PTI, RUE in DMP; a and b in Nup; c_1 in LAI and, A and B_d in ETc, two of the parameters that decreased its importance with the growth and development of the crop was c_2 in (LAI, ETc, and DMP); k in all outputs, this temporal variation were also reported by López et al. (2012) with NICOLET model for lettuce and SUCROS model applied to husk tomato (López et al., 2014), also Wang et al. (2013) showed this variation along the crop growth and the variation with the increase of the uncertainty of the parameters for WOFOST model applied for corn crop.

The cardinal temperatures T_{max}, T_{min}, T_{ob}, and T_{ou}, Figures (2, 3, 4, 5) were influential on the performance of the model, particularly at the beginning of the fructification, however, these parameters were not selected for the parameter estimation technique, because, these were defined for tomato crop according to

Chu et al. (2009), Peet and Welles (2005), Soltani and Sinclair (2012) which were obtained by experimentation, other parameters as k (extinction coefficient) and d (crop density) were also not considered, though showed high sensitivity in the analysis, because the k parameter could be measured with a ceptometer and the density of the crop (d) was defined before setting the experiment. During this analysis was found that these two parameters are the most sensible in all outputs, because of these are strongly related to the light interception and this concept was used to compute the DMP, LAI, and ETc and therefore the Nup that depends on DMP, the effect of these parameters were discussed by De Reffye et al. (2009) who say that limitations occur for light interception when density is low because the expression of light interception assume a homogeneous distribution of leaves.

Therefore, the parameters that finally were considered for their calibration were; RUE, a, b, c_1 , c_2, A, B_d, B_n and, $PTIini$. RUE parameter explains the quantity of carbon assimilated converted to total dry biomass, therefore, was important for DMP and Nup because both variables are correlated. For models with the light-use efficiency approach this parameter and k become more important as was found for CERES-maize model (DeJonge et al., 2012) and WOFOST model studied by Dzotsi et al. (2013), SALUS model for maize, peanut and cotton reported by Wang et al. (2013), and AZODYN for wheat crop (Makowski et al. 2006), all of them found higher values of S_{Ti} and S_i for RUE and k. The parameters a and b are important in the quantification of nitrogen uptake, the increasing of the indices of these two parameters and RUE from the days 40 after growth to the end of the crop are explained with the increasing of the slope of the exponential growth curve of the total dry matter production due to the fruits filling and this fact increased the demand for nitrogen by the crop. c_1 and c_2 explain the expansion of area foliar, the indices for c_2 decrease over the time due to the LAI reach the maximum value for LAI of the crop (the plateau of the curve of this variable was reached) however, c_1 raised its importance over the time. On the other hand, A, B_d and B_n have an effect on the radiation and VPD in the estimation of the crop transpiration, the second and third parameters were not significant in this analysis carried out with the data of spring-summer, this similar result was found by Sánchez et al. (2008), however, these authors found that for autumn-winter season become important, for this reason, were considered as a significant parameters, the parameter $PTIini$ (one of the two initial condition) did not have high values for S_{Ti} and S_i, but we realized that it improved the performance of the calibration of the other selected parameters. Since the values $S_{Ti} - S_i$ are a measured of the participation of the parameter X_i in interaction with another factor (Saltelli et al., 2008), considering the 20% of uncertainty of the parameters at the end of the crop growth these values were calculated for all parameters selected for the parameter estimation, so the difference between two indices were for RUE (0.004), a (0.010), b (0.015), c_1 (0.004), A (0.010), B_d (0.01) only the parameters that did not have interaction were c_2 and $PTIini$, B_n.

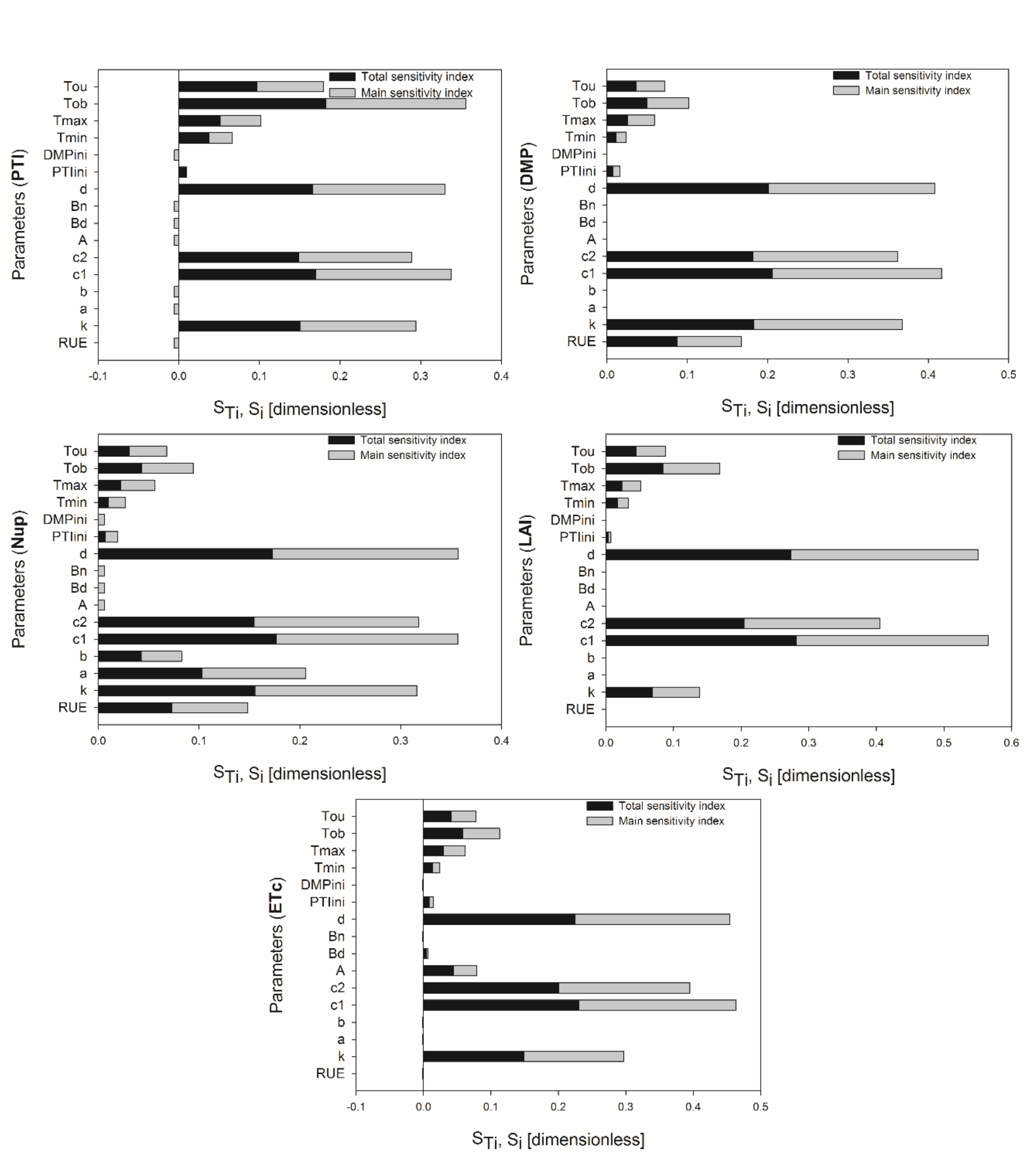

Figure 6 .2 Sensitivity indices estimated using Sobol's method for PTI, DMP, Nup, LAI and ETc for 10% of parameters variation after 40 days of growth.

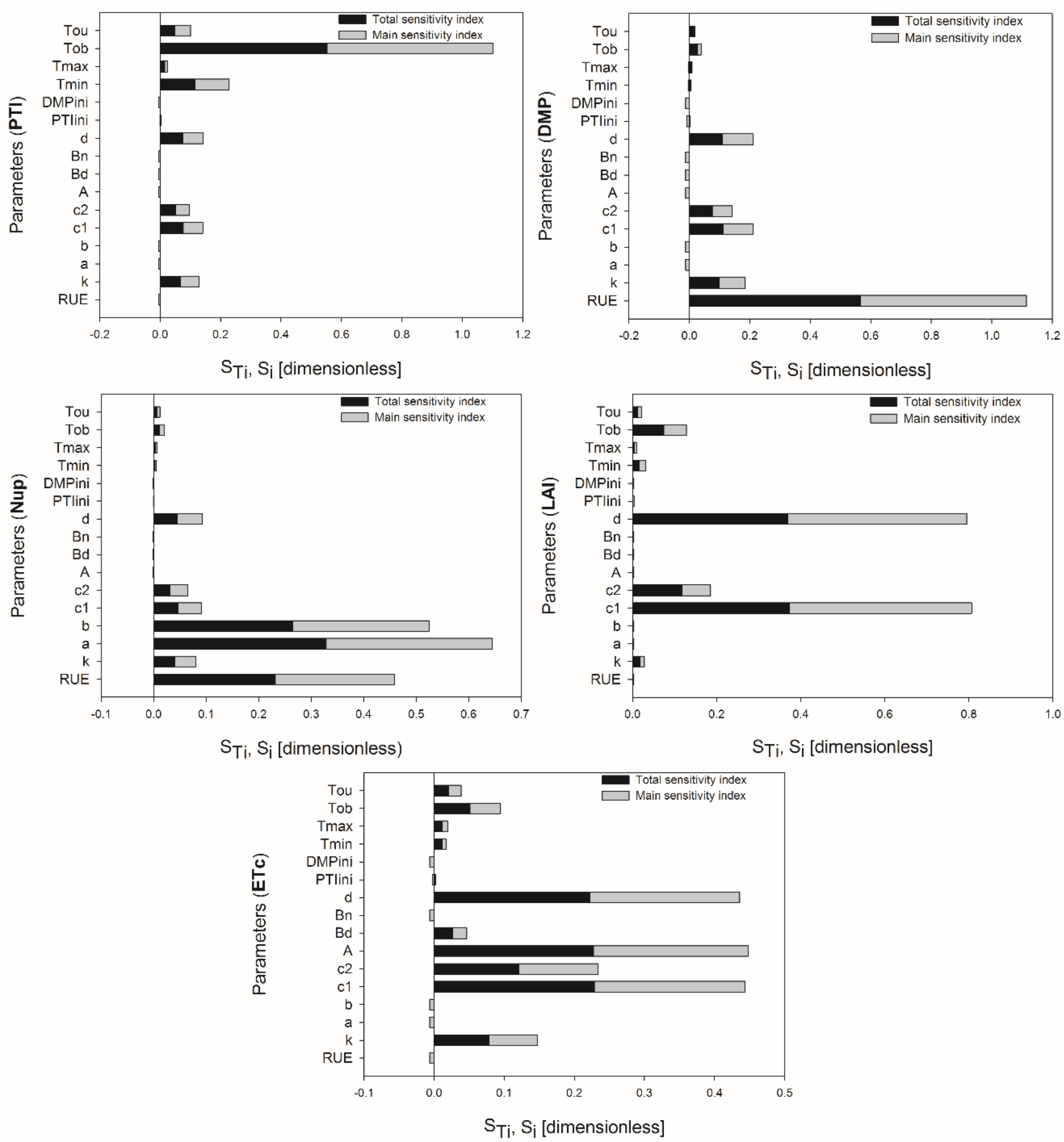

Figure 6 .3 Sensitivity indices estimated using Sobol’s method for PTI, DMP, Nup, LAI and ETc for 10% of parameters variation at the end of growth cycle (119 DAT).

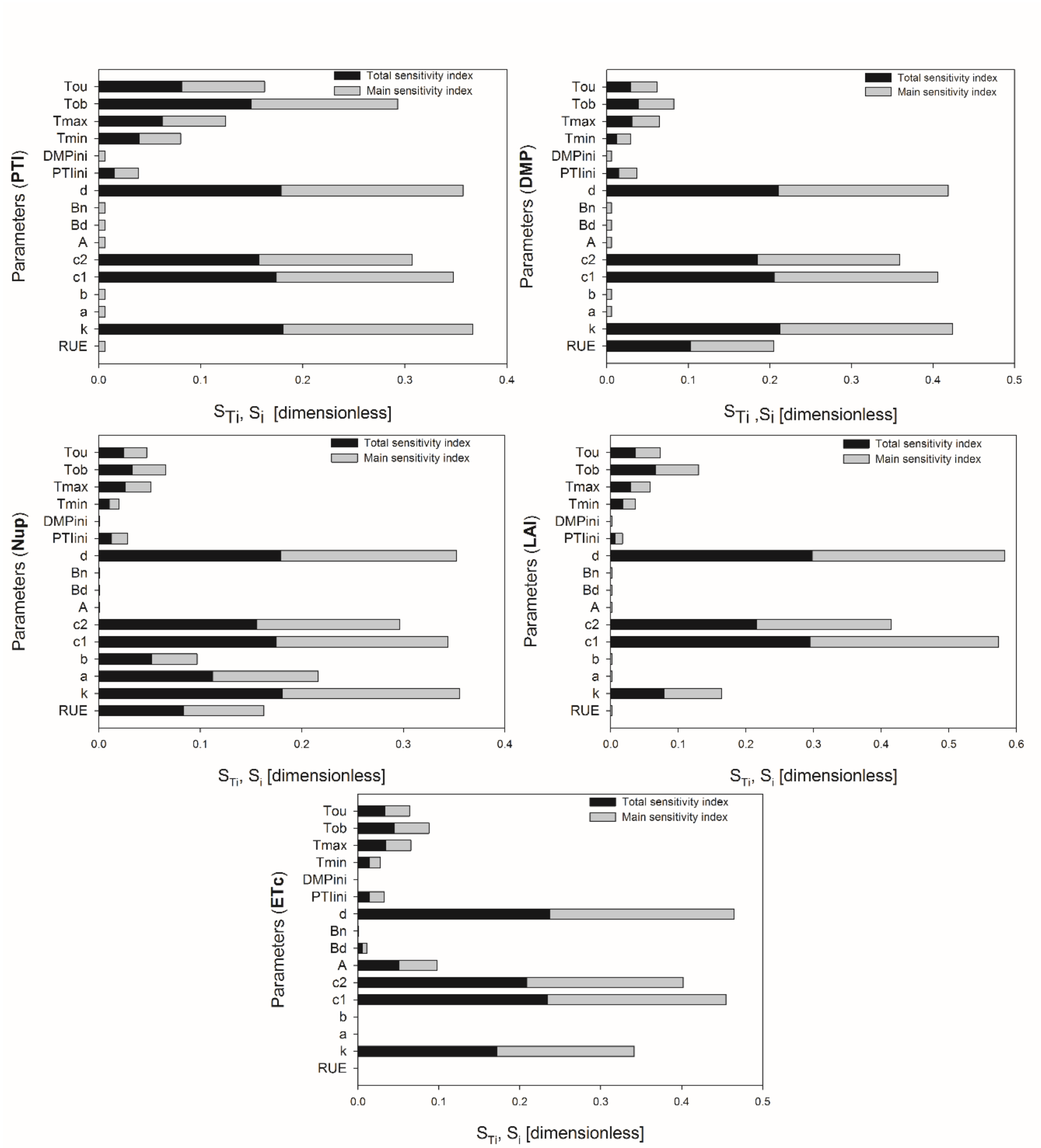

Figure 6 .4 Sensitivity indices estimated using Sobol's method for PTI, DMP, Nup, LAI and ETc for 20% of parameters variation after 40 days of growth.

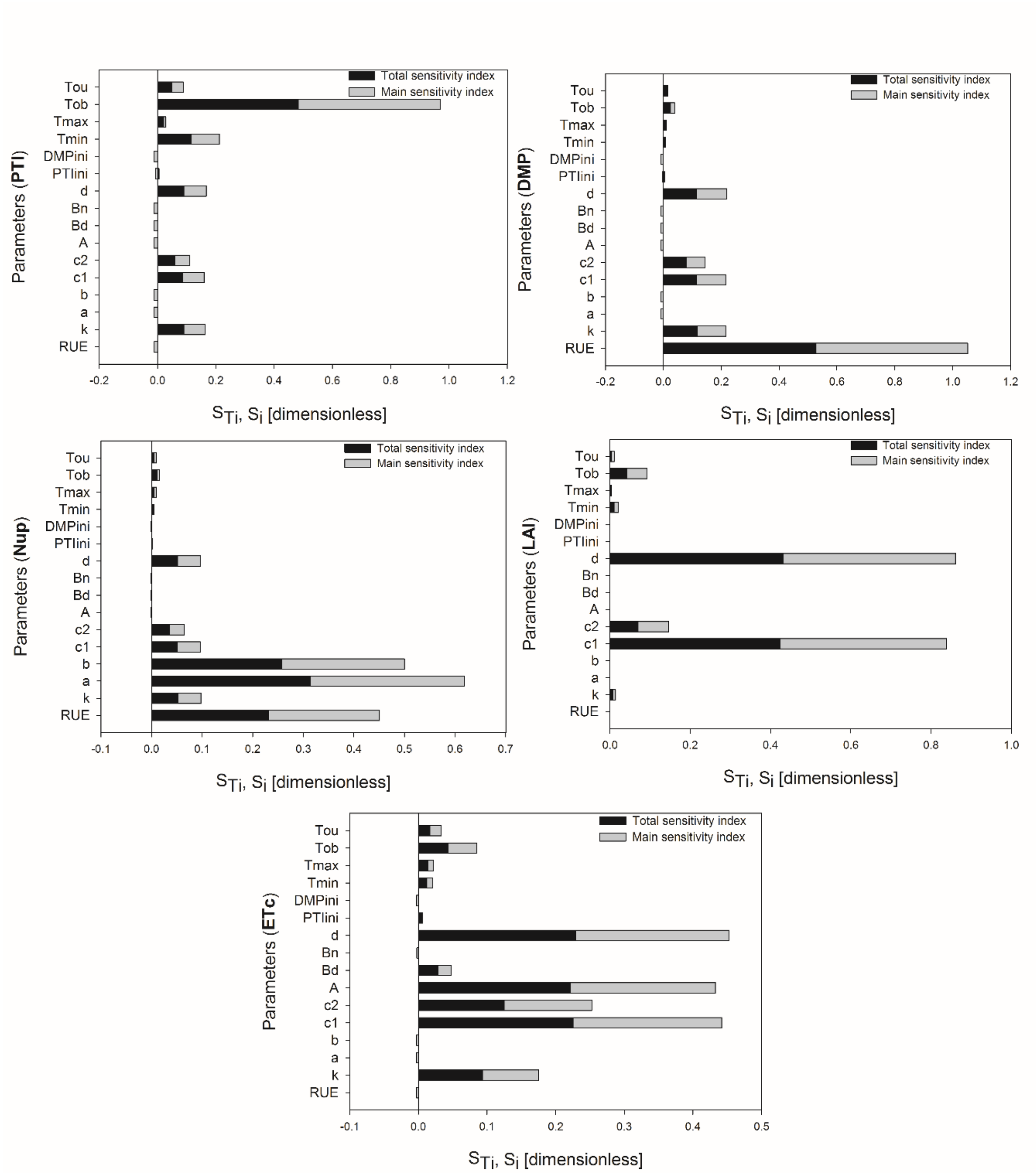

Figure 6 .5 Sensitivity indices estimated using Sobol's method for PTI, DMP, Nup, LAI and ETc for 20% of parameters variation at the end of growth cycle (119 DAT).

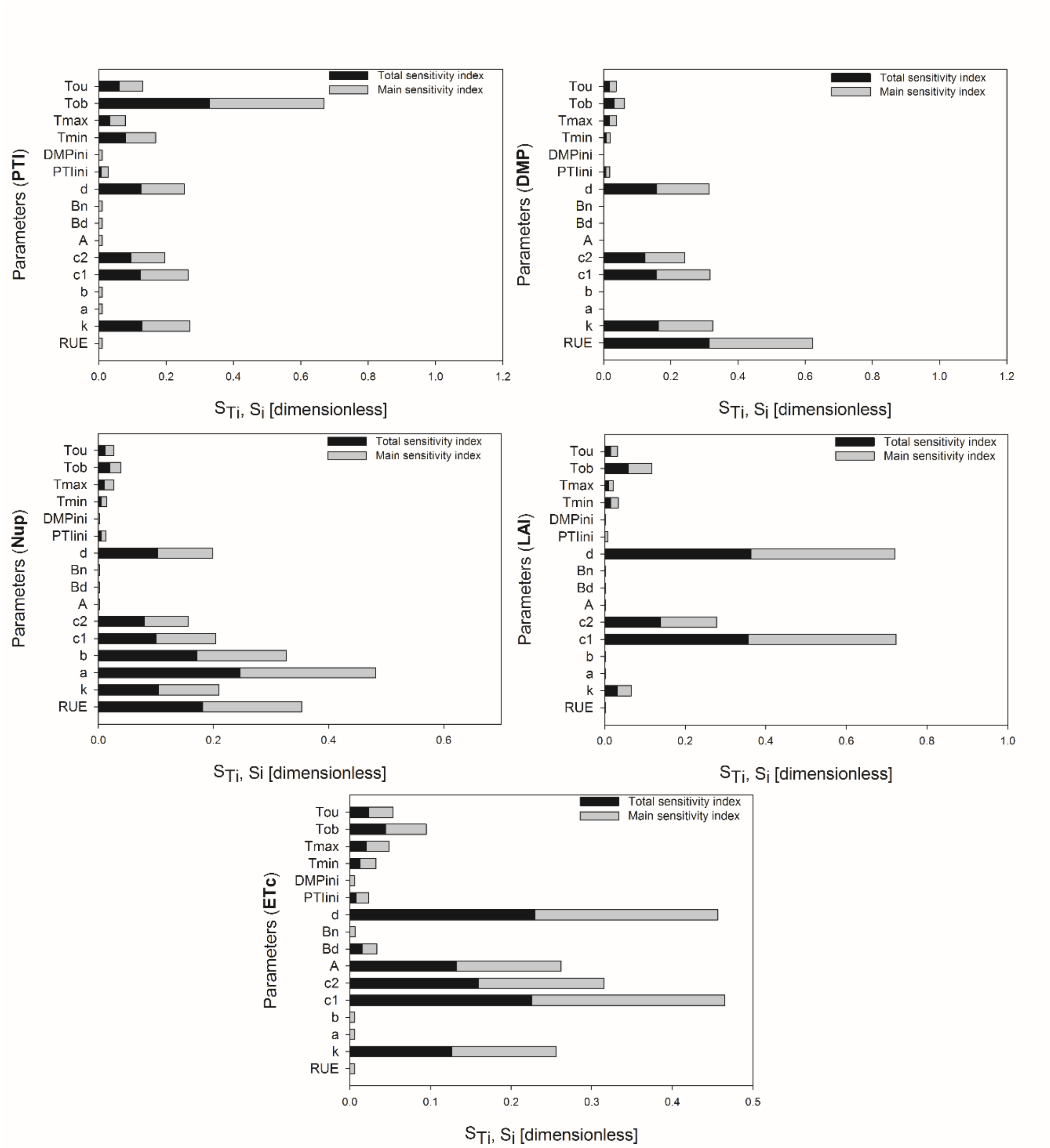

Figure 6 .6 Sensitivity indices estimated using Sobol's method for PTI, DMP, Nup, LAI and ETc for 20% of parameters variation integrating the daily values of the outputs until the end of growth cycle (119 DAT).

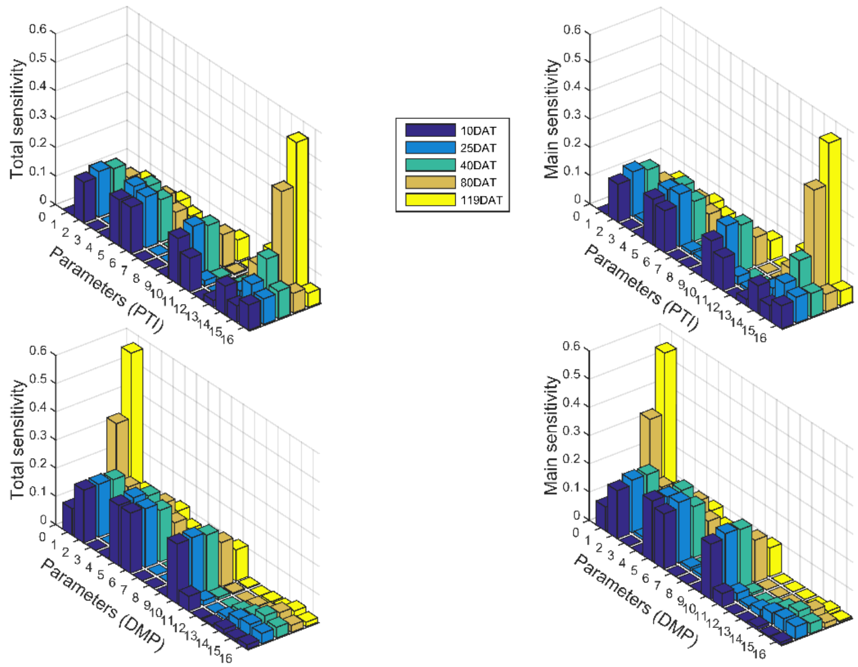

Figure 6 .7 Temporal variation of the sensitivity indices estimated using Sobol's method for PTI, DMP for 20% of parameters variation.

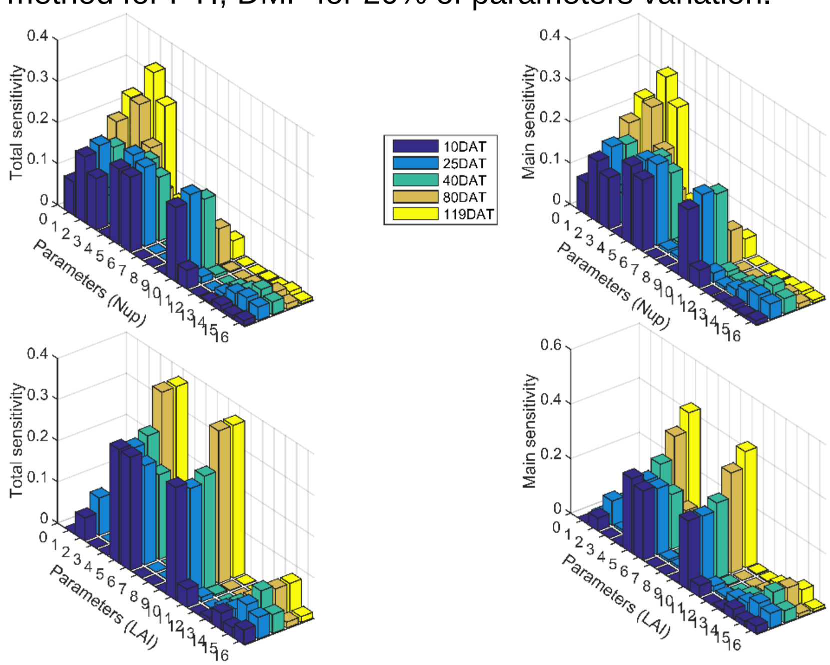

Figure 6 .8 Temporal variation of the sensitivity indices estimated using Sobol's method for Nup, LAI for 20% of parameters variation.

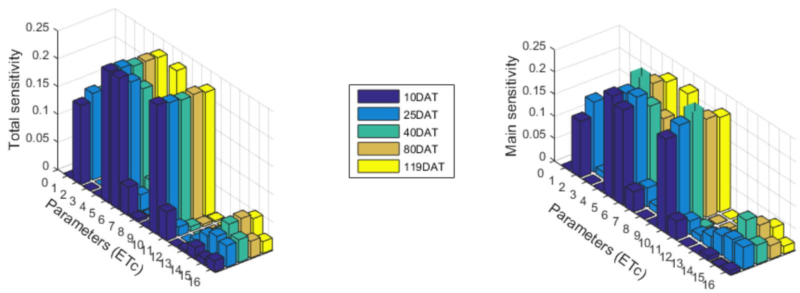

Figure 6 .9 Temporal variation of the sensitivity indices estimated using Sobol's method for ETc for 20% of parameters variation.

Table 6.4 Sensitive HortSyst input parameters in order of decreasing of total and first order Sobol's sensitivity ($\boldsymbol{S_{Ti}}$ and $\boldsymbol{S_i}$) for two stage of the tomato crop.

Output response	**At the beginning of fructification**	**At the end of the crop growth**
	Parameters (10% of variation)	
PTI	T_{ob}, c_1, d, k, c_2, T_{ou}	T_{ob}, T_{min}
DMP	c_1 , d, k, c_2, RUE	RUE, c_1, d, k
Nup	d, c_1, c_2, k, a, RUE	a, b, RUE
LAI	c_1, d, c_2, T_{ob}, k	c_1, d, c_2
ETc	c_1, d, c_2, k	c_1, A, d, c_2, k
	Parameters (20% of variation)	
PTI	k, d, c_1, c_2, T_{ob}, T_{ou}, T_{max}	T_{ob}, T_{min}
DMP	k, d, c_1, c_2, RUE	RUE, c_1, d, k
Nup	k, d, c_1, c_2, a, RUE	a, b, RUE
LAI	d, c_1, c_2, k, T_{ob}	d, c_1, c_2
ETc	d, c_1, c_2, k	d, c_1, A, c_2, k

6.3.2 Calibration of HortSyst model by Differential evolution (DE)

The HortSyst crop growth model was calibrated by solving the minimization problem, which can closely match the simulated and observed data of the tomato crop. Nine parameters were estimated and the performances of the model during the calibration for autumn-winter and spring-summer are shown in Figure 11 and 12, the values of the parameters calibrated and the PTI and PTI vs LAI Michaelis-Menten behavior are shown in Figure 10. The statistics goodness of fit of the model are presented in Table 4 and 5. For both seasons the features of In DE method were: population size was 30, the number of parameter estimated was 9, accuracy of 1e-8, generation number of 1000, the minimum values were taken from the mean of 25 runs and the strategy of DE/RAND/1/bin algorithm was implemented during the analysis (Chakraborty, 2008; Das and Suganthan 2011; Price, Storn et al., 2005). F is a constant which affects the differential variation between two solutions and set to 0.6 in our experiments, the value of the crossover rate (CR) was 0.9 which controls the change of the diversity of the population. The better fit according to RMSE were for LAI followed by Nup, DMP, and ETc for both crop season were close to zero, this indicates a good model effectiveness. Another fit index was the efficiency modeling, for all outputs were near to one, this indicated a good model performance according to Brun et al. (2006) and Xuan et al. (2016), with the values of bias found in autumn and winter, the nitrogen uptake was slightly underestimated and DMP, LAI and ETc were overestimated, in case of the season spring and summer season LAI and DMP were underestimated and Nup and ETc were overestimated. Also the plots 1:1 are presented in Figure (11 and 12) to visualize the quality of the prediction of the output responses of the HortSyst model n Figure 11 and 12. All the parameters were calibrated successfully, only the parameter Bn in the transpiration output resulted with high standard deviation during the autumn-winter season (Table 4), this means that it was very uncertain for autumn-winter, but for the spring-summer. The calibrated value of RUE for autumn and winter was higher than found by Gallardo et al. (2014) and for spring and summer was closed to reported by Challa and Bakker (1998) and this values were different between two seasons. a parameter was lower for the two crop period and b was higher than reported by Gallardo et al. (2014) these calibrated values was quite similar for both season, the parameter c_1 were closer for two seasons but c_2 during the spring and summer was more that twice than in autumn-winter, A, B_d parameter was higher than found by Sánchez et al. (2011) either for autumn-winter and spring summer, these parameters to estimate ETc were different between each crop cycle. The HortSyst parameters calibrated using DE algorithm was closer except for

B_n parameter found by Martinez et al. (2017) who used a nonlinear least square method to find the correct values of the parameters for spring-summer.

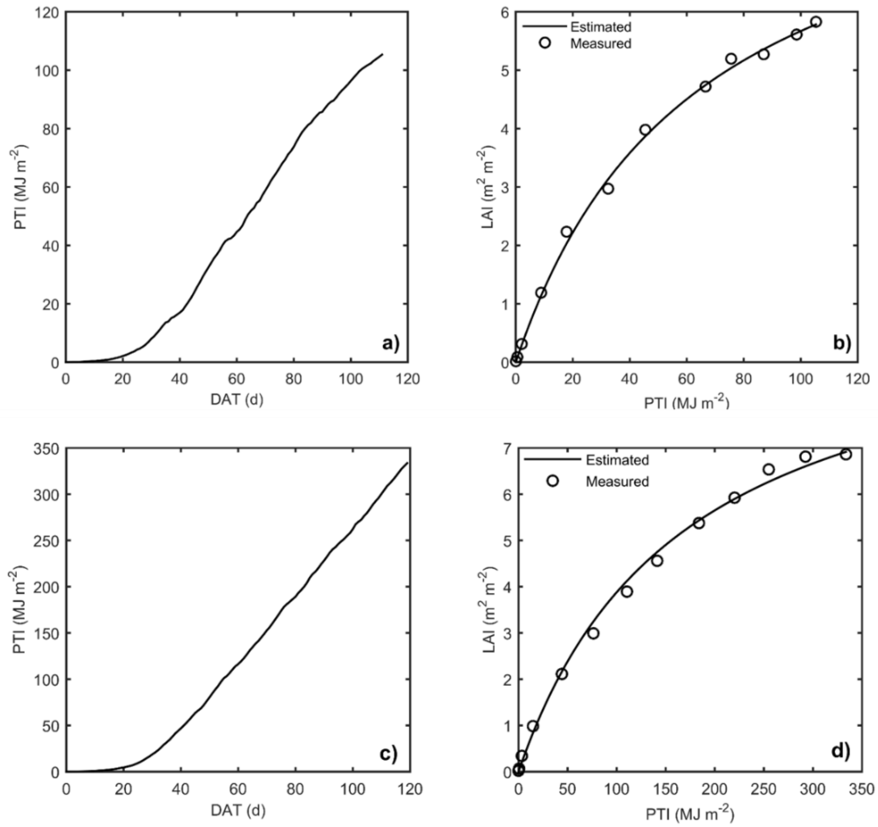

Figure 6 .10 PTI estimated vs measured and simulated of LAI data after calibration for autumn – winter, 2015 a), b) spring-summer c), d).

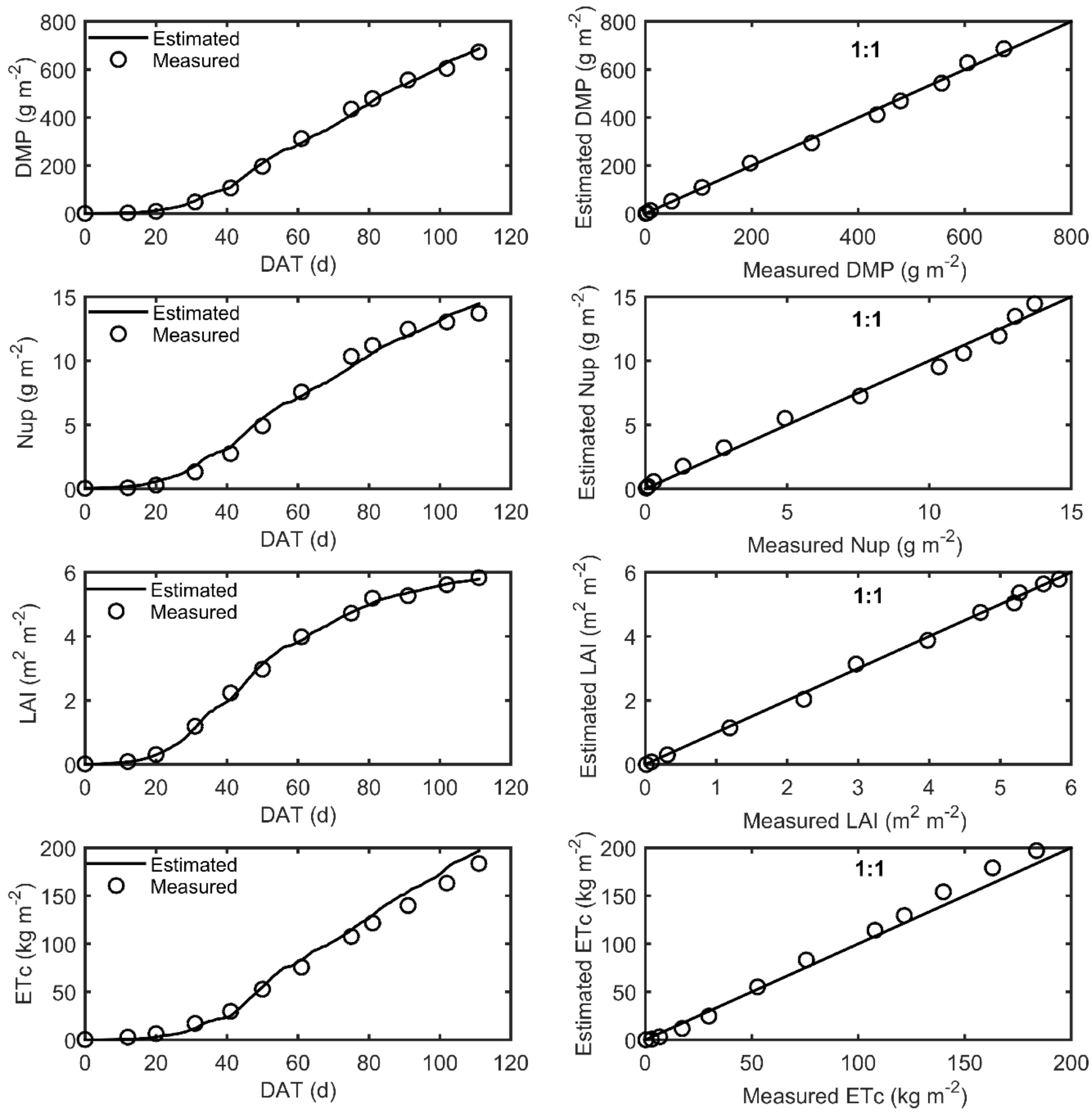

Figure 6 .11 Measured and simulated data after calibration for the DMP, Nup, LAI and ETc during autumn – winter, 2015.

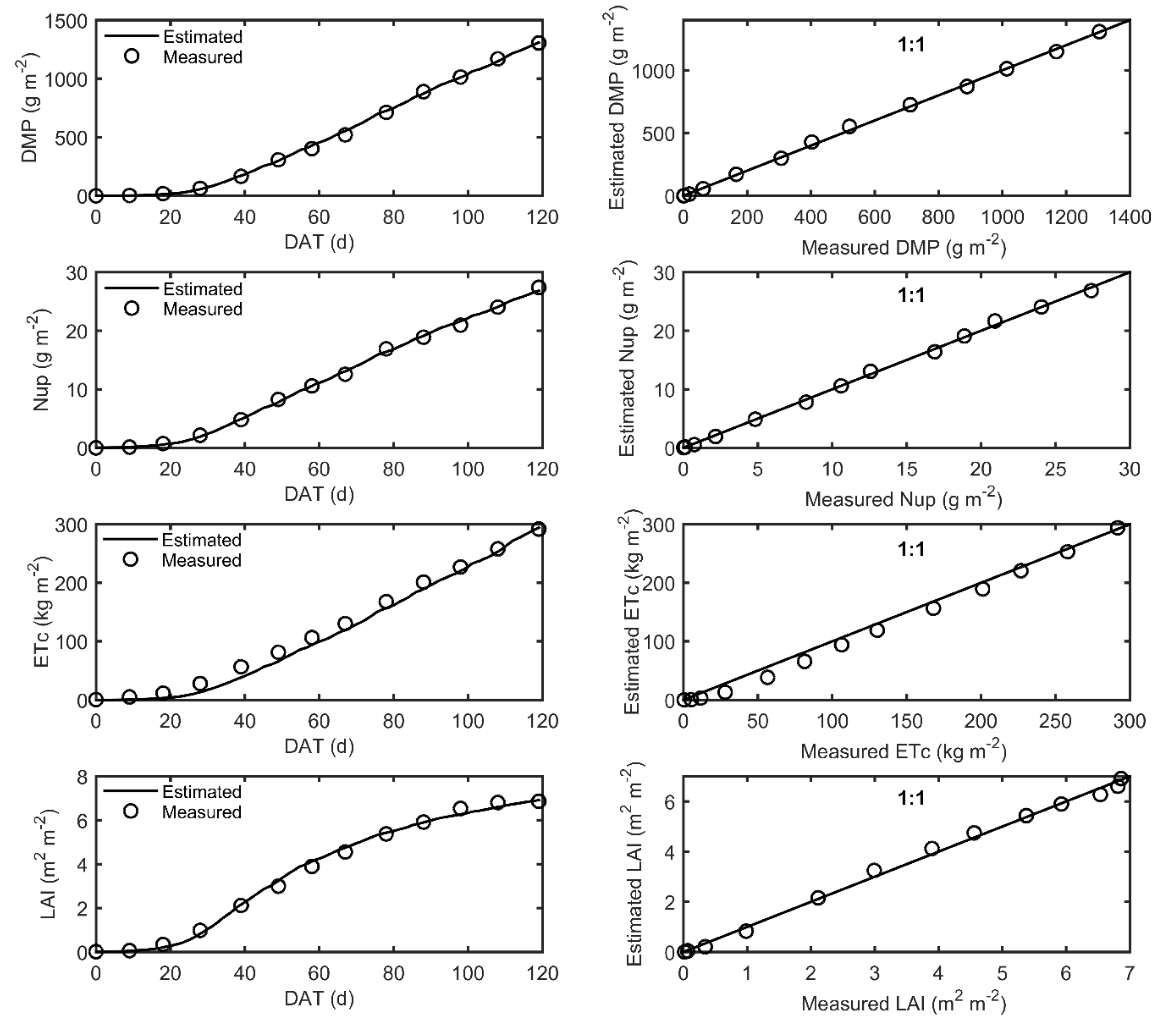

Figure 6 .12 Measured and simulated data after calibration for the DMP, Nup, LAI and ETc during spring – summer, 2016.

Table 6.5 Parameters values and standard deviations after calibration process by means of DE.

Parameters	Nominal values	Autumn-Winter	Nominal values	Spring-Summer
PTIini	0.03	0.01 (2.05e-9)	0.06	0.031 (4.58e-9)
RUE	4.01	4.79 (3.81e-7)	3.10	2.99 (2.10e-7)
a	7.55	5.89 (1.23e-5)	7.55	5.68 (7.34e-6)
b	-0.15	-0.19 (4.06e-7)	-0.15	-0.17 (2.23e-7)
c1	2.82	2.65 (4.02e-8)	3.07	2.97 (3.52e-8)
c2	74.66	63.46 (1.26e-9)	175.64	167.99 (8.85e-13)
A	0.30	0.63 (4.58e-9)	0.49	0.56 (2.40e-9)
Bd	18.70	28.57 (1.99e-7)	11.20	15.69 (2.18e-7)

Bn	8.50	4.73 (4.45)	8.28	16.51 (6.13e-7)

Table 6.6 Statistics of goodness of fit resulting from calibration of model for autumn-winter and spring-summer.

Outputs	**Autumn -Winter**			**Spring - Summer**		
	Bias	RMSE	EF	Bias	RMSE	EF
DMP	0.41566	13.3133	0.9970	-1.5437	14.7602	0.9989
Nup	-0.0708	0.5004	0.9909	0.0287	0.3583	0.998
LAI	0.0249	0.0989	0.9979	-0.0007	0.1564	0.99623
ETc	3.6465	39.3297	0.8153	1.29181	28.206	0.9581

6.4 Conclusions

The global sensitivity analysis based on Sobol's method allowed determining the most influential parameters in HortSyst model, the values found in the parameters during the calibration were the correct values for the autumn – winter and spring-summer season, which the quantity of radiation between two crop seasons were different and were reflected in the dry matter production and leaf area index. It was necessary the parameter estimation for each crop period. These parameter values could be used to simulate another greenhouse crop as reference values when non-limitation of water and nutrient exist. However, more experiments are needed to validate this model using this parameter estimated and also more research is needed to extend this model to another crop under greenhouses.

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7. A DECISION SUPPORT SYSTEM FOR FERTIGATION MANAGEMENT BASED ON A GROWTH AND TRANSPIRATION MODEL FOR GREENHOUSE-GROWN TOMATOES

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Abstract

Today, agriculture has the challenge of dealing with the integration of productivity, product quality, and environment preservation. These objectives are sometimes conflicting with maximum yield, which often requires the application of large amounts of nitrogen fertilizer, increasing the risk of nitrogen leaching. Growers must therefore adapt new fertilization strategies to achieve a desired production, and quality, but also environmental protection. Thus, it is valuable to develop precision irrigation and fertilization management practices based on temporal and spatial variability of the system by using decision support systems. An experiment was carried out during autumn-winter, in which a tomato (*Solanum lycopersicom* L.) crop "CID F1" was grown in a hydroponic system, with a density of 3.5 plants m^{-2}. Plants were transplanted on August 21, 2015. A HOBO weather station (Onset Computer Corporation) was installed inside of the greenhouse. Temperature and relative humidity were measured with a S-TMB-M006, and global radiation was measured with a S-LIB-M003 sensor. In the experiment, three plants were chosen randomly for the sample every ten days to measure dry matter, leaf area index, and nitrogen uptake accumulation. Crop transpiration was measured every minute by means of a weighing lysimeter located in a central row of the greenhouse. The device includes an electronic balance (scale capacity =120 kg, resolution ± 5 g) equipped with a tray carrying four plants for the experiment. The recently developed HortSyst dynamic model, in discrete time, which predicts dry matter production, nitrogen uptake, leaf area index, photo-thermal time, and crop

transpiration can be used for nitrogen management and irrigation scheduling in soilless tomato culture in Mexican greenhouses. Based on this dynamic model, a decision support system can be developed that could be used to help greenhouse growers to improve their current fertigation practice. So far, the HortSyst model has been calibrated and evaluated for a tomato crop; however, it can be easily applied to other greenhouse crops.

Keywords: DSS model, horticultural systems, irrigation programming, simulation model, water consumption

7.1 Introduction

During the last two decades, a number of decision support programs for horticulture have been developed by scientific institutes or commercial firms. Several crop-growth mathematical models for horticulture greenhouse crops have been developed by scientists. Depending on the primary purpose of a specific model, a wide variety of different modelling approaches are used. Most of the models have been proposed in order to simulate the influence of one or a few main input factors. With an increased interest on knowledge based on systems, the idea of developing a decision support systems came up for special crops based on expert systems and artificial intelligence techniques. There has been some hopes that it would be possible to include all relevant variables of a crop system, like plant nutrition, irrigation scheduling, pest control, temperature control, work capacity, and economy in one decision support system (Lentz, 1998). Today, agriculture has a new challenge to deal with: the integration of productivity, product quality, and environmental preservation. These objectives sometimes conflict with maximum yield, which often requires the application of large amounts of nitrogen fertilizer, increasing the risk of nitrogen leaching (Nkoa et al., 2003). Growers must therefore adapt new fertilization strategies to offer production, quality, and environmental protection. Thus, it is valuable to develop precision irrigation and fertilization management practices based on temporal and spatial variability of the crop system (Chen et al., 2015) by using a decision support system. Under fertigation conditions there are some questions related to the distribution of the fertilization dose during the crop cycle, according to its demands and depending on its different phonological stages. The nutritional demand can be estimated according to the water requirements through the cumulative curve of consumptive use (transpiration), whose temporal behavior is closely related to the development of the crop (Alonso et al., 2003). On the other hand, the crop growth is calculated as a function of the production of biomass (dry weight accumulation) (Li et al., 2009; Shibu et al., 2010; Stockle et al., 2003, Gallardo et al., 2016). Then, the uptake of nutrients by the crop during the cycle is quantified (Bechini et al., 2006; Gallardo et al., 2014; Le Bot et al., 1998; Nkoa et al., 2003). In soilless growing systems, the reservoir of water and nutrients in the root zone is limited. It follows that it is necessary to synchronize plant water demand in the short term, avoiding deficiency or salinization in the growth medium. Thus, mathematical models for transpiration depending on greenhouse climate have been developed, parameterized, and validated and these models have been probed as an accurate irrigation method for cucumber and tomato soilless culture for saving water. Because of the increasing areas under irrigation and the high water requirements of crops (which consume around 70% of water available to human beings). The scarcity of water resources is leading to increasing controversy about the use of water resources by agriculture and industry, for direct human consumption, and for other purposes. Such debate could be alleviated by improving crop water use efficiency, so that increasing water use efficiency of crops is becoming a main goal for agriculture and food security goals. Nowadays, water and nutrients supply of greenhouse crops is mainly based on time or in the integration of solar radiation, which means that crop transpiration and nutrient uptake is not taken into consideration. It seems that by taking into consideration crop transpiration prediction and nutrient dynamics in the plant, a more efficient method for irrigation can be devised. The goal of this work is to carry out the calibration of the HortSyst model, which predicts dry matter production, nitrogen uptake and crop transpiration for the autumn-winter season and to propose a decision support system tool based on this model for irrigation scheduling and nitrogen concentration supply for a tomato crop cycle under greenhouse.

7.2 Material and methods

7.2.1 Experimental setup

The experiment was carried out in a research facility located at the University of Chapingo, Mexico (20° 19’ N, 98° 53’ W, and 2240 m) during the 2015 autumn-winter season. The research was carried out in a chapel type glass greenhouse with dimensions of 8 m x 8 m and a north–south orientation. A tomato crop (*Solanum lycopersicom* L.) "CID F1" was grown in a hydroponic system. Plastic bags with a capacity of 10 liters were used, which were filled with "tezontle" (volcanic rock) substrate with a density of 3.5 plants m^{-2}. Tomato plants were transplanted on August 21, 2015. A drip irrigation systems was used, with a 0.4-m spacing between emitters; the emitters discharge rate was 8 L h^{-1}. The nutrient solution was prepared according to (Pineda et al., 2011; Steiner, 1961), where macronutrient concentration (me L^{-1}) was as follows: NO_3^-:12, $H_2PO_4^-$:1.5, K^+:7.5, Ca^{2+}:9, Mg^{2+}:4: SO_4^{2-}:7, and micronutrient concentration (mgL^{-1}) was Fe^{2+}:2, Mn^{2+}:1, Zn^{2+}: 0.2, Cu^{2+}:0.1.

7.2.2 Climatic variable data measurements

A HOBO weather station (Onset Computer Corporation) was installed inside the greenhouse. Temperature and relative humidity were measured with an S-TMB-M006 model sensor placed at a height of 1.5 m. Global radiation was measured with an S-LIB-M003 sensor located 3.5 m above the ground. Both sensors were connected to a U-30-NRC datalogger, which recorded data every minute. All data were taken from the central rows of the greenhouse.

7.2.3 Crop variable data measurements

In the experiment, three plants were chosen randomly for sampling every ten days to measure dry matter, nitrogen uptake accumulation and leaf area index. Plants were dried out for 72 h at 70 °C. And nitrogen was determined by the

Kjeldahl method (Chapman, and Pratt, 1961). The leaf area Index was determined by nondestructive and destructive methods consisting in taking four plants randomly in order to get measurements of the width and length of the plant leaves and the total leaf area was measured using a plant canopy analyzer LAI-3100 (LICOR, USA). From the measurements, nonlinear regression models were fitted in order to estimate this variable. The crop transpiration rate was measured every minute by means of a weighing lysimeter located in a central row of the greenhouses. The device includes an electronic balance (scale capacity =120 kg, resolution ± 5 g) equipped with a tray carrying four plants. The weight loss measured by the electronic balance was assumed equal to the crop transpiration.

7.2.4 HortSyst model description

The dynamic equations and main modifications are given as follows:

$$PTT(k+1) = PTT(k) + \Delta PTT \tag{1}$$

$$DMP(k+1) = DMP(k) + \Delta DMP \tag{2}$$

$$N_{up}(k+1) = N_{up}(k) + \Delta N_{up} \tag{3}$$

$$\Delta PTT(k) = \left(\sum_{i=1}^{24} TT(i) \right) / 24 \times PAR(k) \times f_{i-PAR} \tag{4}$$

where PTT $(MJm^{-2}d^{-1})$ is the photo-thermal time (Dai et al., 2006; Xu et al., 2010), DMP ($g\ m^{-2}$) is the dry matter production and N_{up} ($g\ m^{-2}$) is the Nitrogen crop uptake. The increment of the photo-thermal time ΔPTT $(MJm^{-2}d^{-1})$ is calculated as the product of the daily normalized daily thermal time by the intercepted daily PAR by the crop canopy, k is daily and i is hourly simulation. In contrast to the cumulative thermal time (CTT), which was used in the VegSyst model (Gallardo et al., 2014), in the HortSyst model, the photo-thermal time was used (Dai et al., 2006; Xu et al., 2010). The normalized thermal time (TT , °C) is defined as the ratio of the growth rate under conditions of actual and optimum temperature conditions (Soltani and Sinclair, 2012; Wang et al., 2013; Xu et al., 2010):

$$TT = \begin{cases} 0 & (T_a < T_{min}) \\ (T_a - T_{min})/(T_{ob} - T_{min}) & (T_{min} \le T_a < T_{ob}) \\ 1 & (T_{ob} \le T_a \le T_{ou}) \\ (T_{max} - T_a)/(T_{max} - T_{ou}) & (T_{ou} < T_a \le T_{max}) \\ 0 & (T_a > T_{max}) \end{cases} \tag{5}$$

where T_a, $T_{\min}$ =10 ºC, $T_{\max}$ 35 ºC, T_{ob} =24 ºC, T_{ou} =27 ºC are the air, top lower, top upper, optimum minimum and optimum maximum, and temperature for crop growth, respectively.

$$PAR(k) = 0.5 \times R_g \tag{6}$$

where R_g (MJ m^{-2} d^{-1}) is the daily global radiation above the crop and (parameter) is PAR fraction of R_g .

$$\Delta DMP = RUE \times f_{i-PAR} \times PAR(k) \tag{7}$$

where RUE (dimensionless) is the parameter radiation use efficiency parameter.

Another major difference between VegSyst and HortSyst is the calculation of the fraction of daily intercepted PAR (f_{i-PAR}) by using the exponential function instead of very complex light interception functions (Gallardo et al., 2014).

$$f_{i-PAR} = \left[1 - \exp(-k \times LAI(k))\right] \tag{8}$$

where *k* is the extinction coefficient. Daily Leaf Area Index was modeled in HortSyst model using the photo-thermal time concept (Dai et al., 2006; Xu et al., 2010). It is worthwhile to mention that LAI is not modelled in the VegSyst model (Gallardo et al., 2016).

$$LAI(k) = \left[\frac{c_1 \times PTT(k)}{c_2 + PTT(k)}\right] \times d \tag{9}$$

where LAI, the leaf area index ($m^2\ m^{-2}$), c_1, c_2 are model parameters, d is the density of planting in the greenhouse.

$$\Delta N_{up} = \frac{\%N(k)}{100} DMP(k) \tag{10}$$

The Nitrogen content is calculated by the following equation (Le Bot et al., 1998; Tei et al., 2002):

$$\%N(k) = a \times DMP^b(k) \tag{11}$$

where a and b are calibration parameters obtained from experimental data. In contrast to the VegSyst model, the transpiration model developed by (Baille et al., 1994; Martínez et al., 2012; Medrano et al., 2011) was incorporated in the HortSyst model.

$$ETc(k+1) = \sum_{i=1}^{24} ETc(i) \tag{12}$$

$$ETc(i) = A \times (1 - \exp(-k_{ext} \times LAI(k))) \times Rg(i) + LAI(k) VPD(i) B_{(d,n)} \tag{13}$$

where $ETc(k+1)$ ($kg\, m^{-2} d^{-1}$) is the daily accumulated transpiration, $ETc(i)$ ($g\, m^{-2} 15\min^{-1}$) is the hourly transpiration rate, VPD is the vapor pressure deficit and A (dimensionless) refers to the radiative parameter; and B_d , B_n ($Wm^2 kPa^{-1}$) are parameters of the aerodynamic term of equation (13) for day and night, respectively. Table 1 shows all the calibrated parameters of the HortSyst model. HortSyst model is a potential growth crop model. The HortSyst model was programed in Matlab environment.

7.2.5 Calibration and measuring of goodness of fit

An appropriate method to perform model calibration is the nonlinear least squares estimation (Brun et al., 2006). A parameters vector p minimize the sum of square errors.

$$\hat{p} = \arg\min J(p) \tag{14}$$

$$J(p) = \sum_{h=1}^{L} \sum_{i=1}^{M} (\bar{y}_h(t_i, p) - y_h(t_i))^2 \tag{15}$$

where $\bar{y}_h(t_i, p)$ is the simulated output, in time t_i , $y_{hj}(t_i)$ is the measurement y_h in time t_i, L is the number of outputs, M is the number of measurements, p is the parameters set of calibration and $\hat{p}$ is the parameter that reduces $J(p)$ to a minimum.

The performance of the two models was evaluated using the root mean squared error (RMSE) and the mean absolute error (MAE), and statistics bias (BIAS) was defined as follows (Brun et al., 2006):

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(Y_i - \hat{Y}_i)^2} \tag{16}$$

$$MAE = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\left|Y_i - \hat{Y}_i\right| \tag{17}$$

$$BIAS = \left(\frac{1}{N}\right)\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right) \tag{18}$$

where N is the number of measurements, Y_i is the measured value for situation i and $\hat{Y}_i$ is the corresponding value predicted by the model.

7.3 Resuts and discussion

7.3.1 Model calibration results

Figures 1 and 2 show the output variables of dry matter production, nitrogen uptake, transpiration, and leaf area index in a glass greenhouse during autumn-winter, 2015. Valdés et al. (2014) report results closer for DMP using the STICS model, but higher values for nitrogen uptake (20 gm^{-2}) and similar values for transpiration according to Gallardo et al. (2014). These figures show that all variables simulated by the model have a good fit against the measurements. The estimated parameter values are the following: for dry matter production a value of RUE (4.65 g MJ^{-1}) was obtained, which is a value slightly higher than those reported by Gallardo et al. (2014) but lower than that (3 g MJ^{-1}), reported by Challa and Bakker (1999). In case of nitrogen uptake, its parameters resulted with values of the a coefficient of 4.8. This value is lower than the value of 7.559 found by Gallardo et al. (2014), slightly higher than what was found by Tei et al. (2002b), and closer to the value of 4.53 reported by Tei et al. (2002a) and Valdés et al. (2014) for tomato. The b coefficient value was -0.1488, which is closer to the value reported by Gallardo et al. (2014) but is about half to the value found by Tei et al. (2002a, 2002b) and Valdés et al. (2014). Likely, these differences are due to the fact that their research was carried out in soil production. For crop transpiration, the parameter A value was 1.1848, Bd 1.369×10^{-6} and Bn 24.2374. In the case of LAI, the coefficient values were c_1 2.7974 m^2 and c_2 74.2475. It is worth mentioning that for tomato LAI, Wang et al. (2017) and Xu et al. (2010) found that this approach generates better results on LAI dynamic estimation than using node development (Bacci et al., 2012; H. Wang et al., 2017).

The best statistics results (Table 1) were obtained for LAI (RMSE, 0.10 m^2m^{-2}) followed by Nup (0.53 gm^{-2}), ETc (1.89 kgm^{-2}) and finally by DMP (13.59 gm^{-2}). However, the last two variables, the simulated and measured values, represent larger numerical values versus Nup and ETc, so taking this detail into account the best adjustments actually correspond to ETc and DMP. According to BIAS statistics, the results for DMP (-2.19) and ETc (0.46) were higher than Nup (-0.08) and LAI (-0.03), which means that the model slightly overestimates the DMP variables and slightly underestimates the ETc with respect to the measured data.

Table 7.1 Statistics of goodness of fit resulting from calibration of model

Output variables	**BIAS**	**MAE**	**RMSE**
DMP	-2.19	11.85	13.59
Nup	-0.08	0.48	0.53
ETc	0.46	1.67	1.89
AI	-0.03	0.09	0.10

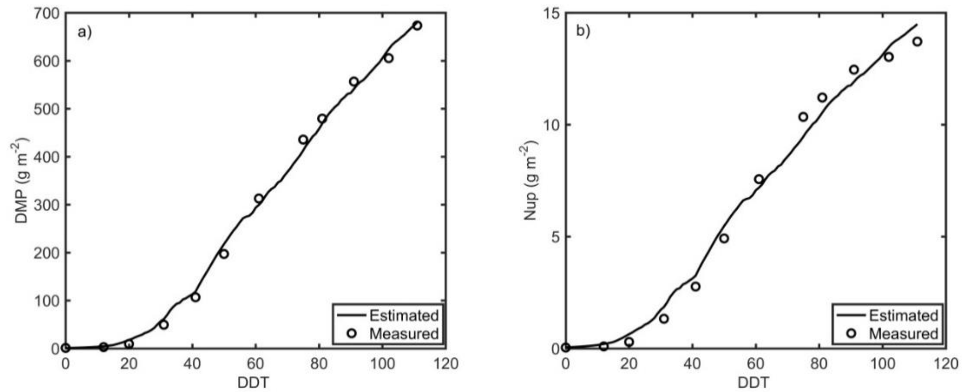

Figure 7 .1 Time course of the simulated and measured values of dry matter production a) and nitrogen uptake b) of a greenhouse tomato crop grown in Chapingo, Mexico, for autumn-winter, 2015.

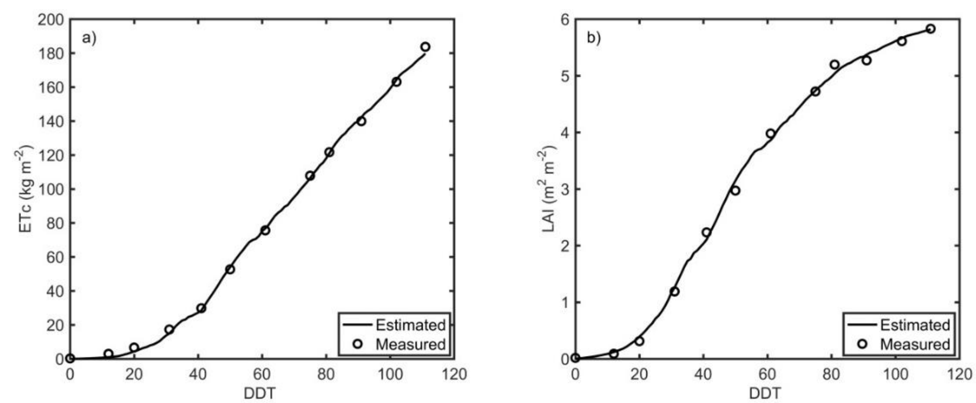

Figure 7 .2 Time course of the simulated and measured values of crop transpiration, a) and leaf area index, b) of a greenhouse tomato crop grown in Chapingo, Mexico, for autumn-winter, 2015.

7.3.2 Irrigation scheduling

The model, besides predicting the daily transpiration, also predicts transpiration every 10 min, 15 min, 30 min or every hour, depending on the frequency of the water supply. In case it is used in crops in soilless culture (Martínez et al., 2012), it is advisable to use the model for simulated values every 10 or 15 min. As an example of the simulation of the transpiration variable for every 15 minutes, Figure 3 shows thirteen simulated days with sunny and cloudy days. The simulated daily values of transpiration cannot be used to schedule the irrigation events in hydroponic systems. Since in these systems the irrigations are applied with a high frequency and a low flow, it is necessary to obtain the simulated values for these variables with shorter time intervals. In order to devise a proposal in the management of irrigation for hydroponic crops, as mentioned by Wang et al. (2017), who intended to obtain a transpiration model to implement greenhouse automatic water management (Massa et al., 2011; Sigrimis et al, 2001), based on knowledge of the crop water demand combined with automatic irrigation technology, two simulated days of transpiration were chosen: a cloudy day with low transpiration (Figure 4) and a sunny day with high transpiration (Figure 5). In the first case, two values of volume were specified as setpoints to be replenished at each irrigation event, 120 mL and 150 mL to reach the container capacity, resulting in three irrigations and four irrigations, respectively. In case of the sunny days, 250 mL and 400 mL setpoints were considered, which resulted in 11 irrigations and 7 irrigations, respectively. The hours in which these irrigations resulted are presented in Table 2. When the accumulated transpiration has reached the setpoints between 8:00 pm and 07:00:00 am of the next day, the first irrigation should be fixed at 07:00:00 am for the next day, and after that the model will continue quantifying the transpiration.

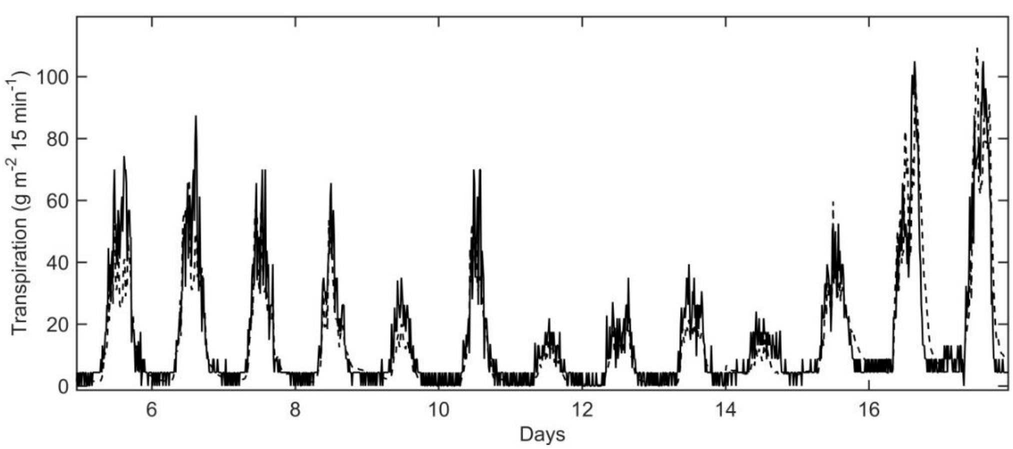

Figure 7 .3 Results of simulation model for crop transpiration (…...Predicted, ___ Measured).

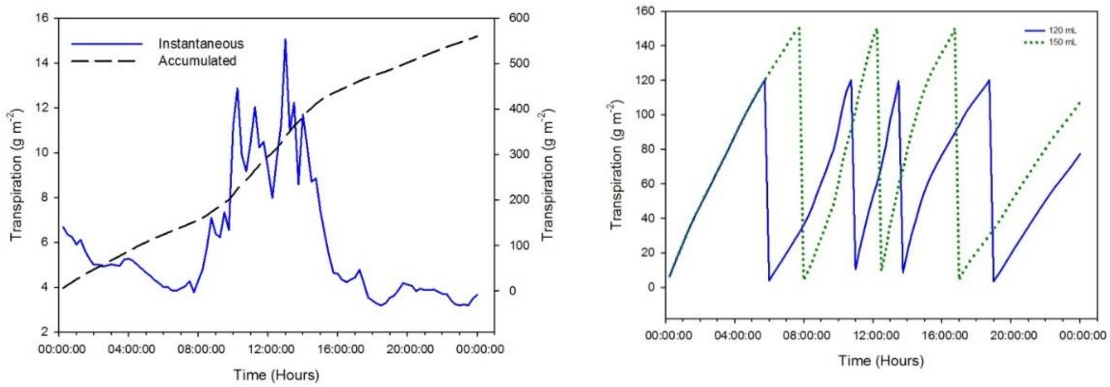

Figure 7 .4 Transpiration for a cloudy day (left) and irrigation scheduling during the cloudy day (right), with LAI 1.7

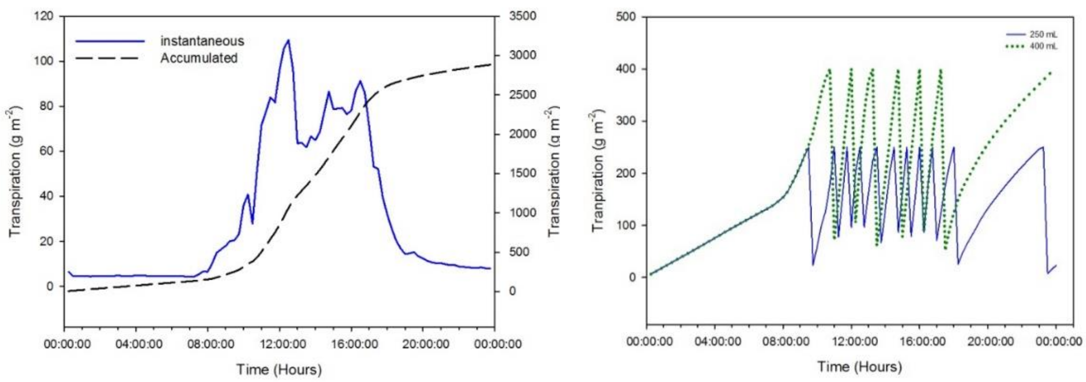

Figure 7 .5 Transpiration for a sunny day (left) and irrigation scheduling during the sunny day (right), with LAI 3.5

Table 7.2 Irrigation management proposal for a cloudy and a sunny day.

IRRIGATION	**cloudy day**		**sunny day**	
	120 mL	**150 mL**	**250 mL**	**400 mL**
R1	07:00:00	07:45:00	07:00:00	07:00:00
R2	10:45:00	12:15:00	09:30:00	10:45:00
R3	13:30:00	16:45:00	11:00:00	12:00:00
R4	18:45:00		11:45:00	13:15:00
R5			12:30:00	14:45:00
R6			13:30:00	16:00:00
R7			14:30:00	17:15:00
R8			15:15:00	
R9			16:00:00	
R10			16:45:00	
R11			18:00:00	

7.3.3 Nitrogen management

For N management in the nutrient solution, it is necessary to know the daily volume of transpired water by the crop. Since N uptake is known to be directly correlated with crop transpiration (Gallardo et al., 2014), the model simulates this variable and nitrogen uptake with acceptable fit on a daily basis (Figure 1), so that the calculation of daily concentration of N uptake by the crop, with a direct calculation between these two variables simulated by the model is feasible to give a management recommendation (Figure 6). The management of N with concentrations calculated daily does not allow to do a nutrient solution for day requirements, because the fertilizer mixing equipment is not capable of preparing the nutrient solutions with that level of detail, and has not yet been developed, so it is necessary to take into consideration an average concentration in each time interval according to its rate of change during the evolution of crop growth. The development of the crop, for this purpose, Figure 6 shows the temporal variation of the concentration of nitrogen dependent on transpiration, and three management proposals are proposed in the concentrations for Nitrogen (Table 3). Firstly, considering an efficiency of 100%, where there was no waste of water and fertilizer, would imply to steer the crop with zero drainage; with the second efficiency, 80% to 70%, we are taking into account 20% and 30% of waste. According to these proposals it is apparent that with the 100% and 80% efficiency the concentrations are below the values 12 me L^{-1} recommended by Urrestarazu (2004) and Steiner (1961), decreasing up to 50% of the recommended concentration after 45 DDT and for the proposal with 80% efficiency, in the first 30 DDT the values in the Table 3 exceed in 3.6 meL^{-1} to the recommended concentration, and after 45 DDT the values are lower. Thus, using concentrations simulated by the model, six levels of management concentrations throughout the development cycle of the crop were determined (Table 3).

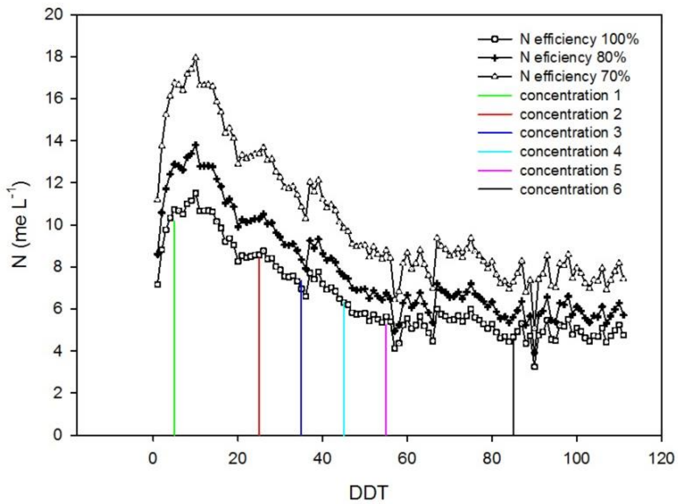

Figure 7 .6 Nutrition management proposal for a tomato crop during the autumn-winter season.

Table 7.3 Management proposal for nitrogen supply under three efficiency levels

Concentrations	**DDT**	**N (me L^{-1}) Efficiency (100%)**	**N (me L^{-1}) Efficiency (80%)**	**N (me L^{-1}) Efficiency (70%)**
1	5	10.0	12.0	15.6
2	25	8.4	10.1	13.1
3	35	7.4	8.8	11.5
4	45	6.3	7.6	9.8
5	55	5.4	6.4	8.4
6	85	4.8	5.7	7.5

7.4 Conclusions

According to the proposal made for the management of irrigation in this research, the developed HortSyst model is capable of predicting transpiration with good precision, in order to be used for scheduling irrigations according to the development of the crop and the variation of climatic conditions inside the greenhouse; because, under cloudy or sunny conditions the model automatically adjusts the numbers of irrigations according to the loss of water by crop transpiration. For the nitrogen management, with the calculation of daily transpiration and nitrogen uptake (depending of the simulated biomass), the model can clearly determine the concentration of this element on a daily basis with good precision and provide useful information for decision making in managing tomato crop nutrition. The mathematical structure of the HortSyst model is quite simple, so it is practical to use the model as a decision support system in the management of greenhouse-grown tomatoes.

7.5 Reference

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8. GENERAL CONCLUSIONS

- The greatest contribution of this research was the development of a relatively simple mathematical model with few parameters and considering climate variables that are commonly measured inside a medium technology greenhouse, the advantage of this model is that it has a physiological and physical support. The mathematical structure was also analyzed and evaluated.
- The HORTSYST dynamic model developed and applied for tomatoes in Mexican greenhouses had an excellent fit to the data measured during the experiment and was found to have a simpler mathematical structure than the VEGSYST model and the predictive quality of the model using the literature values exceeded the model developed for Spain greenhouses (VegSyst). This was confirmed by comparing the values of the RMSE, Bias and EF statistics found in the simulation of both models, with experimental data for both the autumn-winter and spring-summer cycle.
- The submodel that relates the leaf area index and the concept photo-thermal coupled to the HortSyst model showed satisfactory results in the prediction of this variable and improved significantly in the prediction of dry matter production and transpiration, since the index of leaf area is involved directly in the calculation of these two variables.
- The nitrogen and daily dry matter production predicted by the model were acceptable when were compared with the data collected during the experiments.
- The Baille model for determining the transpiration of the crop used in the HortSyst model for irrigation management purposes was simpler compared to the Penman-Monteith model used in the VegSyst model and the predictions of this variable was better in the model HortSyst.
- With the calibration of the model using the method of nonlinear least squares, it was possible to find the correct values of the parameters that

are involved in the mathematical structure of the model, so that the values of the output variables (DMP, Nup, LAI, and ETc) improved greatly.

- With the methods applied for the determination of uncertainty in the predictions of the HortSyst model were obtained satisfactory results, according to which one can rely on the capacity of the model in the predictions of the most important variables that are linked to the production of the tomato crop. On the other hand, the GLUE method (Bayesian approach) proved to be a good tool for these types of analyzes since it does not only consider the simulations but also includes data measured to obtain the statistics that help to determine the predictive capacity of the model.
- According to the proposal made for the using of the model for irrigation programming and nitrogen management, it was concluded that the HortSyst model is a fairly simple model that could be integrated into a decision support system to assist to the growers in the monitoring of the production of tomatoes in greenhouses.
- This model could be adapted to other crops in greenhouse and of course could also improve considering a crop under stress for water and nutrient and other nutrients.