SCIENTIFIC NOTE

Use of dynamic simulation and Forrester diagrams to describe the growth of lettuce (*Lactuca sativa* L.) under field conditions

Uso de simulación dinámica y diagramas de Forrester para describir el crecimiento de lechuga (*Lactuca sativa* L.) en condiciones de campo

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ABSTRACT

The use of computational tools to describe some processes of crop growth has evolved in recent decades and remains an area of active research, where more and more applications are incorporated with the integration of a greater number of mathematical tools, statistics, and computational calculation efficiency, simplifying the tasks of modeling and visualizing the components of the system used. The present research proposes a dynamic growth model for lettuce cultivation using Forrester diagrams to evaluate different scenarios involving five growth functions and five lettuce cultivars in field conditions of the Bailadores region (Venezuelan Andes, 2550 m a.s.l.). The lettuce variety Coastal Star achieved the greatest accumulation of dry matter used as a response in each model. The logistics of growth function was properly adjusted to the experimental data compared to the other models. The proposed diagram model can be used as a basis for the construction of more complex models that incorporate other physiological variables of the crop and the growth environment.

Key words: state variables, maximum system capacity, Vensim.

RESUMEN

El uso de herramientas computacionales para describir algunos procesos del crecimiento de los cultivos ha evolucionado en las últimas décadas y sigue siendo un área de investigación activa, donde se incorporan cada vez más aplicaciones con la integración de una mayor cantidad de herramientas matemáticas, estadísticas y de eficiencia de cálculo computacional, simplificando las tareas de modelado y las de visualización de los componentes del sistema utilizado. La presente investigación propone para el cultivo de lechuga un modelo de crecimiento dinámico utilizando diagramas de Forrester, para evaluar diferentes escenarios involucrando cinco funciones de crecimiento y cinco variedades de lechuga en condiciones de campo de la región de Bailadores (Andes venezolanos, 2550 m s.n.m). La variedad de lechuga Coastal Star fue la que logró la mayor acumulación de materia seca (usada como respuesta en cada modelo). Se encontró que la función de crecimiento logístico ajustó adecuadamente los datos experimentales en comparación con los otros modelos. El modelo diagramado propuesto puede ser usado como base para la construcción de modelos más complejos que incorporen otras variables fisiológicas y el ambiente del cultivo.

Palabras clave: variables de estado, máxima capacidad del sistema, Vensim.

Introduction

Agricultural systems are complex and exhibit a multitude of input and output variables that may exhibit complex relationships with patterns not easily described (Namirembe *et al*., 2020). The advancement of computer systems is a tool for the management of information derived from crop fields. When this information is processed using mathematical or statistical models together with computational tools, the results of the adjustment of suitable models can guide decision-making in the management of crops in favor of optimal resource use and increased food production. At present, there are countless models available in the scientific literature that address specific aspects of agricultural production, highlighting water management, nutrients, pests, and diseases (Negus *et al*., 2024). Crop development models can be divided into two types: mechanistic and empirical (El Jarroudi *et al*., 2014). Mechanistic models mathematically describe our knowledge and hypotheses about the physiological processes of the crop and their interactions with their development in the environment (Landsberg & Sands, 2010). Empirical models apply statistical models of crop development, describing the cumulative processes based on the involved parameters in the functional form that is used. These models are generally adapted to agricultural field data (Junk *et*

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al., 2016) and their primary application is the prediction of the development of growth under certain regional and climatic conditions for some plant varieties. The suitability of these models for a particular farmer will depend on his individual needs (Kundathil *et al*., 2023). The dynamic nature of crop development related to their phenological stages has allowed the use of dynamic simulation models for more than a decade to describe and evaluate plant growth (Hernández *et al.,* 2009) and to explain their ecophysiological relationships and their changes due to adverse factors (Sommer, 2023). However, defining growth is complex in nature, as it is the result of a multitude of interrelated processes, among which division, elongation, and specialization of cells stand out as well as several external factors, such as plant species, soil, moisture, light, nutrient availability, agricultural management, etc. (Hilty *et al*., 2021; Logachev & Goncharov, 2024; Rauff & Bello, 2015; Van Keulen, 2013).

There are several methods for analyzing plant growth; the functional approach is one of the most important. This may generate some confusion due to the existence of a specific field of mathematics that deals with functional analysis and can generate confusion from a semantic viewpoint, since the growth approach does not use the tools of functional analysis at all. Therefore, the phrase "fit functional forms" is recommended (Kantorovich & Akilov, 2016). In this approach, measurements are taken at discrete time intervals and include mathematical functions that are used to describe the growth of plants or their structures (Hunt, 2016), using all the data collected during the sampling process that covers morphometric, physiological, soil and climatic variables to identify the functional form that could properly fit the data (Alvar-Beltrán *et al*., 2023).

It is appropriate to use Forrester diagrams to represent the dynamic process of crop modeling (Haefner, 2005; Logachev & Goncharov, 2024) since these are an invaluable tool for understanding and analyzing intricate systems, particularly those exhibiting nonlinear dynamics. Forrester diagrams represent a system in a simple way using direct symbology that allows the connection of a series of processes of the systemin an interactive and visual way that facilitates an understanding of the interactions of the different system compartments.

In this type of diagram, eight types of symbols are employed. The first of these corresponds to the state variable (compartments) where the matter or energy of the system is stored, and it is represented by a rectangle. The second symbol represents the flow variables that determine the movements of matter and/or energy between the state variables or another external system. This is represented by a continuous double-line arrow with a key symbol in the middle that allows for the flow velocity to be controlled. The matter and/or energy can be transferred to another level of study or to an external system that is referred to as a source or sink. This is represented by a cloud figure that is the third symbol. The fourth symbol represents the auxiliary and exogenous variables that are constant and provide information that facilitate the interpretation of the equations used in the flow variables, and this is represented by a circle. The fifth symbol represents the information channel between exogenous or auxiliary variables, and it is represented by a continuous arrow (Logachev & Goncharov, 2024).

The importance of model development lies primarily in its ability to describe experimental or observational data over time in order to facilitate prediction or its use as a sub-model in more complex models. The selection of models depends on their adjustment; and, in the case of dynamic models, it is necessary to specify the appropriate differential equation. This allows a consideration whether the parameters of the equation are of biological importance (not always directly interpretable) and finally evaluate the metrics associated with differences between observed and estimated values of the model (Hamner *et al*., 2018). In the case of simple models, the differential equation is typically described in terms of the first derivative of the growth function that by means of numerical integration allows an estimate of the parameters of the model of the indicators of growth of plant organs as well as of the whole plant. Among the functional forms of differential equations there is the logistic model of Blumberg, Von Bertalanffy, Richards and Gompertz; however, other models are known to characterize the development of the crops that could be involved (Fernández-Chuairey *et al*., 2019; Reyes-Medina *et al*., 2019; Rodríguez-Perez, 2013).

Models of crop growth have been proposed worldwide and include the cultivation of tomato (*Solanum lycopersicum*) (Luo *et al*., 2020), corn (*Zea mays*) (Attia *et al*., 2021), potato (*Solanum tuberosum*) (Divya *et al*., 2021), lettuce (*Lactuca sativa*), etc. The models are applicable to both field and greenhouse conditions for many crops; however, in the case of lettuce, a leafy crop that has food and medicinal uses leading to an increase in its consumption worldwide, little has been developed in dynamic modeling of field data in tropical conditions (Das & Bhattacharjee, 2020; Díaz-Pérez *et al*., 2024; Lipton & Ryder, 2021). Most simulation models in this field are designed to simulate cultivation under controlled conditions in greenhouses. One such model is the NICOLET model (Nitrate Control in Lettuce) that is well-known and widely used (Chang *et al.*, 2021; Juárez-Maldonado *et al.*, 2010; Jung *et al.*, 2018; Li *et al.*, 2022). Other models of horticultural crops include the DSSAT and SUBSTOR models (Jones *et al.*, 2003; Rodríguez-González *et al.*, 2020; Sarmiento & Bowen, 2002) that have been used in South America with high frequency in the dynamic modeling of potato cultivation.

Because of the aspects described above, this research proposes a model of lettuce (*Lactuca sativa*) cultivation under field conditions using Forrester diagrams for its construction with the separate incorporation of different growth functions for the aerial and root parts of the plant. This represents a preliminary stage in the creation of a more comprehensive model that will be applicable to tropical conditions.

Materials and methods

Location

The research was carried out in the Agricultural and Environmental Biotechnology Research Group (GIBAA) at the National Experimental University of Táchira, Venezuela. The site is located at an elevation of 2,550 m in the region of Bailadores in the Venezuelan Andes, with air temperatures ranging from 9°C to 16°C and an annual rainfall between 1500 and 2000 mm year^{-1}.

Plant material

Five varieties of lettuce (*Lactuca sativa*): V1 - Green Towers, V2 – Thoreau, V3 - Coastal Star, V4 – Arroyo, and V5 – Altura were used in this study. The total biomass (shoots and roots) of 18 plants per variety was measured weekly for 8 weeks. The collected plant material was placed in prelabeled paper bags and then dried at 65°C in a forced-air oven until a constant mass was achieved. The dry matter (g m^{-2}) was determined and expressed as a result of having a field density of 10 plants per m^2.

Implemented model

Simulation and calibration were performed using Vensim software (Professional license version 5.11a). The model was configured with a single compartment or state variable to represent the dry weight of the response variable for each part of the plant (shoot Hs or roots Rs) (Fig. 1). Each compartment has two flows; in the case of leaves (Fig. 1A), the input flow represents gross primary production, and the output flow represents translocation of matter from the aerial parts to the roots. For the roots (Fig. 1B), the input flow is the material coming from the aerial part, while the output flow corresponds to the root exudates.

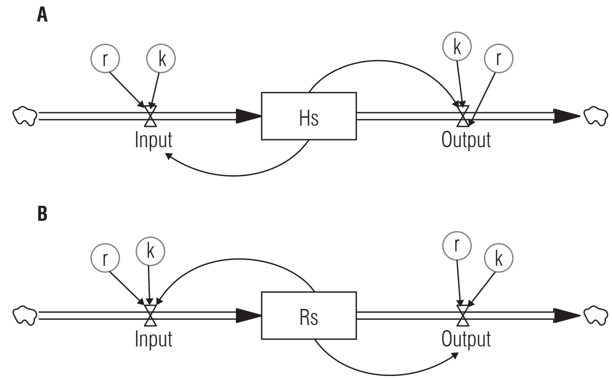

FIGURE 1. Forrester diagram of the proposed model for vegetative growth of the shoot system (A) and the root system (B) of lettuce.

After identifying the state variables and flows affecting each compartment (Fig. 1), five growth functions (Tab. 1) were selected to estimate dry matter accumulation in each compartment over time. For this, the first derivative was used, depending on the flow rates of each compartment. These functions have similarities in that they present the growth rate (r) and a maximum system capacity (k) as auxiliary variables, while the functions of Blumberg and Richards present other parameters related to the turning point where the growth rate reaches its maximum expression (Tsoularis & Wallace, 2002). All functions require as input information the size of the compartment (N) over time that is provided by the information channel (continuous arrows) as well as the auxiliary variables (Figs. 1 and 2).

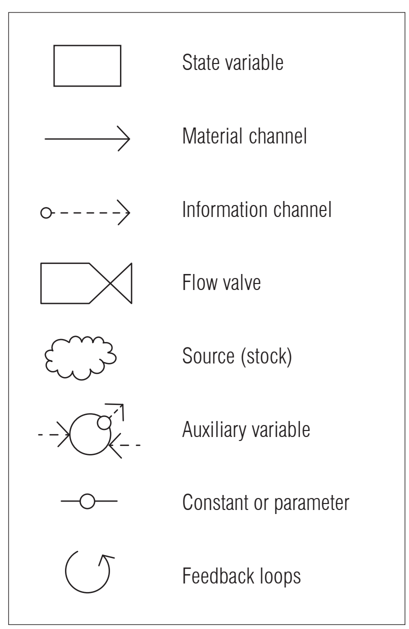

FIGURE 2. Symbols of Forrester diagrams and their interpretations.

TABLE 1. Growth functions and their first applied derivatives (Rodriguez, 2013; Szabelska *et al*., 2010).

Model	Functional form (N(t))	First derivative (*dN/dt*)
Logistic	$\frac{k}{1+\left[\left(\frac{k}{N_0}-1\right)e^{-rt}\right]}$	$rN\left(1-\frac{N}{k}\right)$
Blumberg	$\int_{N_0/k}^{N(t)/k} x^{-\propto}(1-x)^{-\gamma}dx = rk^{\alpha-1}t$	$rN^{\alpha}\left(1-\frac{N}{k}\right)^{\gamma}$
Von Bertalanffy	$k\left[1+\left[1-\left(\frac{N_0}{k}\right)^{1/3}\right]e^{-\frac{1}{3}rk^{1/3}t}\right]^3$	$rN^{2/3}\left[1-\left(\frac{N}{k}\right)^{1/3}\right]$
Richards	$k\left[1-e^{-\beta rt}\left[1-\left(\frac{N_0}{k}\right)^{-\beta}\right]\right]^{\frac{1}{\beta}}$	$rN\left[1-\left(\frac{N}{k}\right)^{\beta}\right]$
Gompertz	$kexp\left\{\left[ln\left(\frac{N_0}{k}\right)\right]^{1-\gamma}+r^{\prime}(-1)^{\gamma}(1-\gamma)t\right\}^{\frac{1}{1-\gamma}}$	$rN\left(ln\left(\frac{N}{k}\right)\right)$

Model fitting

Calibration of the estimated parameters for each growth function used was performed using the calibration module of the Vensim software that provided the simulated values. Given the bivariate nature of the response (dry weight of shoots and root parts), the adjustment tools applied consisted of statistics based on the criterion of approximation of the distance between a set of data points. For this purpose, Euclidean, Manhattan, and Mahalanobis distances were determined. These distances are assessed based on the principle that a lower value indicates a better fit (Haefner, 2005; Hamner *et al*., 2018). The distances were calculated using R (R Core Team, 2023).

Results and discussion

The experimental data showed that varieties V2, V3, and V4 were the ones that achieved the highest weight at the end of the trial, with 460 g m^{-2}, 459 g m^{-2}, and 445 g m^{-2} compared to varieties V1 (362 g m^{-2}) and V5 (411 g m^{-2}). When adding the root dry weights to the shoot dry weights (V1: 107 g m^{-2}; V2: 81 g m^{-2}; V3: 150 g m^{-2}; V4: 121 g m^{-2}; V5: 151 g m^{-2}), V3 obtained the highest total dry weight compared to the others. It should be noted that, in both leaves and roots, an increase in dry matter accumulation was observed from day 40. The results were considerably higher than those reported by Ortiz Mackinson *et al*. (2022), who obtained 150 g m^{-2} dry weight in their optimal treatment for the aerial part, influenced by a multitude of factors, including variety and management, etc.

Model

Plant growth is usually described in three stages (Hilty *et al.,* 2021), starting with germination, followed by a phase of rapid growth known as the logarithmic stage, and finally, a senescence stage. In this research the evaluated stage corresponded to the logarithmic phase, making the proposed model a good descriptor of the process when using the logistic function (Tab. 2). The logistic model was properly adjusted to the experimental data compared to the other functions tested for both variables (Figs. 3 and 4). These results differed from Mathieu *et al*. (2006), who obtains a better description of the experimental data using a second order exponential polynomial.

Computational tools in the modeling processes allowed for the evaluation of different options to describe a process and select equations that provided a good fit during model development (Antle *et al*., 2016). These tools are leading researchers to formulate various hypotheses about growth-related processes (Berger *et al*., 2019; Muller & Martre, 2019). Constantly, strategies are being sought for the selection of materials with specific good performance, using models that describe their development (Zohary, 1991). In this regard, the proposed model can lead to the development of management plans with various aspects such as fertilization timing and planting times (Chiesa *et al*., 2001; Rauff & Bello, 2015), aiming to provide the crop with the necessary resources for its growth. In this case study, growth is most pronounced in both the aerial and root parts after 40 d (Figs. 3 and 4). This approach would allow the determination of crop growth stages that could be used to facilitate a more comprehensive understanding of lettuce growth behaviour (Li *et al*., 2022). This, in turn, would allow the identification of the optimal timing of fertilization that, in turn, would improve growth and yield.

Another case where the logistic model is appropriate was that of Carini *et al*. (2020) who evaluate four different lettuce cultivars. Similarly, Tan *et al*. (2022) demonstrate that

TABLE 2. Distances obtained for each growth function in lettuce.

Distance	Logistic	Richards	Von Bertalanffy	Gompertz	Blumberg
Manhattan	4.72	6.87	11.11	25.28	18.56
Euclidean	1.01	1.54	2.62	6.14	3.38
Mahalanobis	0.09	0.44	0.51	0.91	0.92

the NICOLET B3 model is capable of accurately predicting the fresh and dry matter production of lettuce. Conversely, Li *et al*. (2022) utilise three models to characterise the growth of lettuce crops. Their findings indicate that the Verhulst growth function accurately reflects the observed growth characteristics. However, the logistic function demonstrates a superior fit to the sigmoidal curve derived from the height measurements, suggesting the potential for evaluating different functions according to the specific characteristics of the crop under evaluation. It is important to note that the evaluations presented above correspond to the growth of the crop under controlled greenhouse conditions.

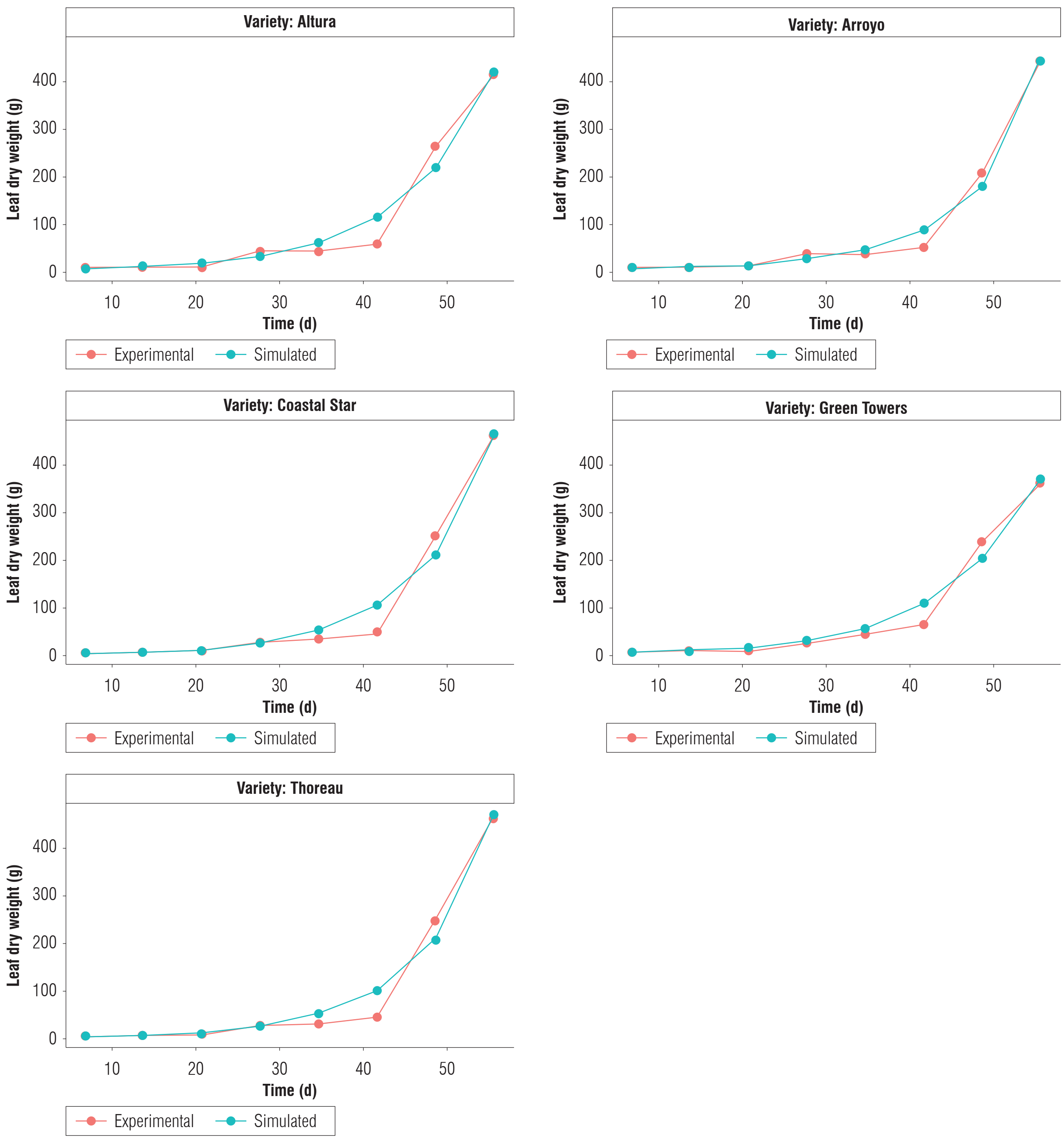

FIGURE 3. Experimental and simulated values for leaf dry weight of lettuce using the logistic growth function.

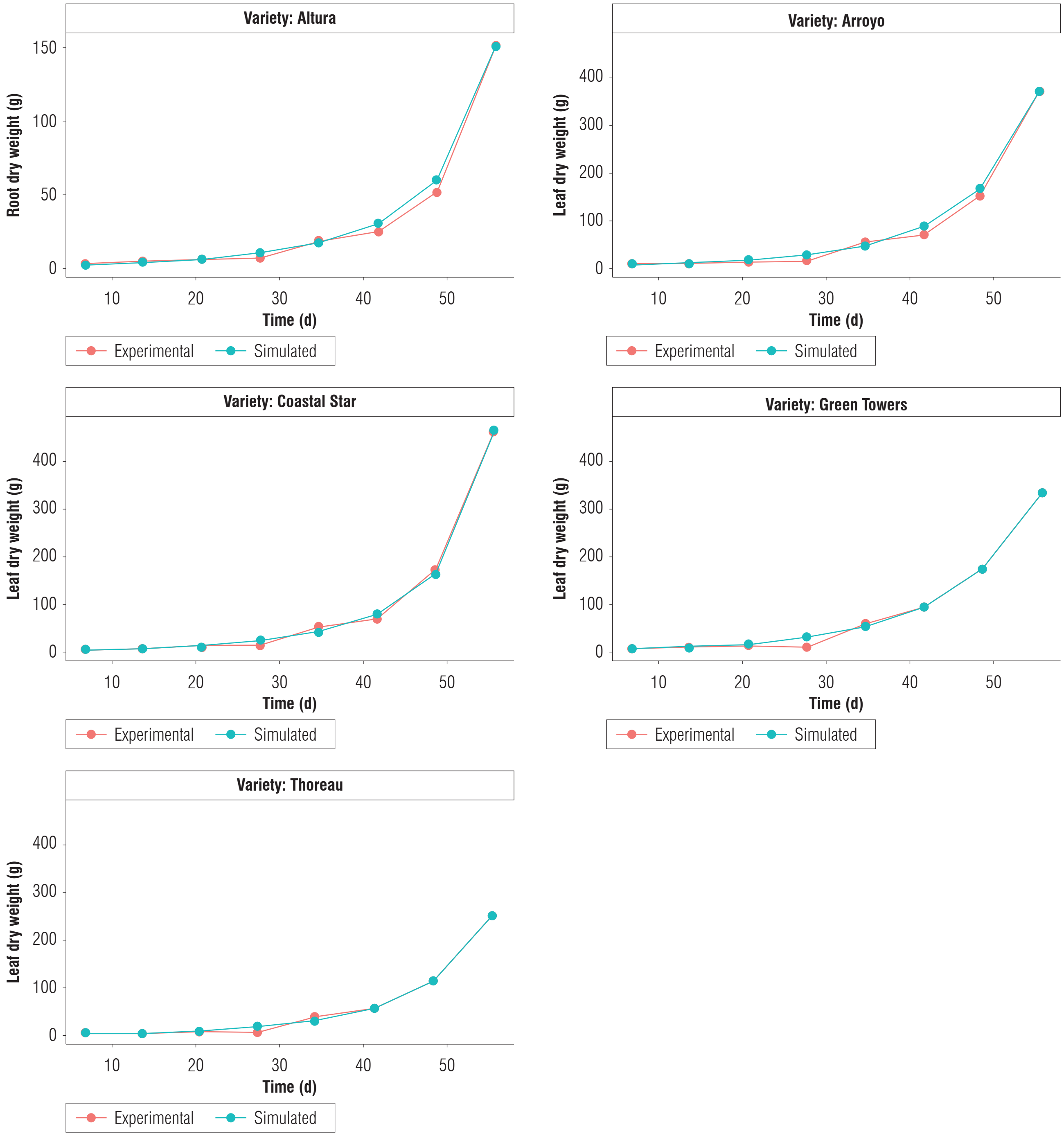

FIGURE 4. Experimental and simulated values for root dry weight of lettuce using the logistic growth function.

The proposed model allowed the comparison of different growth functions; and, although it may be preliminary, it offers scalability, providing the opportunity to evaluate various options and incorporate different conditions as well as other functions, allowing increasingly complex models such as the MOMOS model to evolve, beginning with the description of soil carbon (Pansu *et al.*, 2004; Pansu *et al.*, 2010), involving both soil carbon and soil nitrogen (Pansu *et al.*, 2014).

Conclusions

Dynamic simulation models are a tool for studying the different stages of plant growth by selecting equations and representing biological processes in a more realistic way. In this research, discriminant analysis showed that the logistic growth function had the best goodness of fit for simulating the case study that would allow the identification of growth stages and improve the use of resources and management.

Constructing these types of models with data from high-altitude tropical climates enables the evaluation of agricultural production systems and research into the incorporation of new tools to better utilize environmental resources for food production.

In the teaching of dynamic crop modeling, Forrester diagrams certainly facilitate the interpretation of the components considered in the modeling process, whether this is preliminary in nature or how a sub-model has been used in a more complex model.

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Conflict of interest statement

The authors declare that there is no conflict of interests regarding the publication of this article.

Author's contributions

AV and RT designed the experiments and conducted the field and laboratory experiments. AEDC carried out the statistical analysis of the study. NG and AEDC interpreted the results. AV and RT wrote and translated the initial draft. All authors revised the final version of the manuscript.

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