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## FUZZY MODELING FOR THE ANALYSIS OF DIFFERENT LIGHT INTENSITIES IN THE PRODUCTION OF BELL PEPPER SEEDLINGS

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### KEYWORDS

Supplemental lighting, LED, Fuzzy model.

### ABSTRACT

Bell peppers are one of the most cultivated and consumed vegetables in Brazil, and their high production yield largely depends on the use of high-quality seedlings. Supplementary lighting using light-emitting diodes (LEDs) can help in the production of seedlings and improve their quality. This study aims to develop a fuzzy model to predict the agronomic parameters of bell pepper seedlings under different light intensities. Experimental data on the lighting levels and biometric responses of bell pepper seedlings were used to develop a fuzzy model, and the lighting levels defined in five sets were used as the input variable. The model was used to predict the output variables, namely the plant height, number of leaves, stem diameter, internode number, shoot fresh weight, and root fresh weight. The results indicated that the use of supplemental lighting at a level of  $75 \mu\text{mol m}^{-2}\text{s}^{-1}$  was the most beneficial, producing seedlings with more leaves, higher stem diameters, internode numbers, and fresh weights. The model error rates were satisfactory for the predicted values of all variables, demonstrating the usefulness of the fuzzy model for estimating the best lighting levels in the cultivation of bell pepper seedlings.

### INTRODUCTION

Bell peppers are one of the most cultivated and consumed vegetables in Brazil (Santos et al., 2020). For successful vegetable production, the use of quality seedlings is fundamental to decreasing production risks and increasing productivity (Bezerra, 2003).

The use of supplemental lighting such as light-emitting diodes (LEDs) in plant production has been studied for different species, such as tomatoes (Paucek et al., 2020), strawberries (Díaz-Galián et al., 2021), sweet potatoes (Rahman et al., 2021), and ornamental species (Koksal et al., 2015). In bell pepper production, studies have indicated that supplemental LED lighting can increase the fruit quantity (Joshi et al., 2019), with different light spectrum compositions producing different results (Claypool & Lieth, 2020).

For such situations that involve decision making in complex and uncertain environments, including the agri-

food field, the fuzzy set theory is a promising alternative for solving these problems (Tomasiello & Alijani, 2021). In the agricultural field, fuzzy models have been widely used in several areas, such as to evaluate the effects of different irrigation depths (Gabriel Filho et al., 2022) and salinity (Putti et al., 2022) on the yield of irrigated crops, development of models for the eye temperature of cattle under heat stress conditions (Lins et al., 2021 b) and for the eyeball and crest temperatures of laying hens (Lins et al., 2021 a).

Considering supplementary lighting in protected vegetable cultivation, the use of fuzzy models can be useful for identifying the most suitable intensities for the efficient growth of cultivated crops and enabling the development of intelligent controls.

Therefore, this study aims to develop a fuzzy model to predict the agronomic parameters of bell pepper seedlings under different light intensities.

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## MATERIAL AND METHODS

### Description of the experiment and data used

In this study, employed data from an experiment conducted by Rocha et al. (2014) at the Integrated Regional University of Alto Uruguai e das Missões, URI Erechim Campus, Rio Grande do Sul experimental field, between January 28 and March 5, 2014, was employed.

According to Rocha et al. (2014), seeds were sown in plastic cups of 120 ml. Two seeds were planted per cup in the commercial substrate Plantmax plus vermiculite at a depth of 0.5 cm and ratio of 2:1. Manual irrigation was performed daily according to the plant needs, and the irrigation water was replaced with Hoagland's solution (Hoagland & Arnon, 1950) (Table 1) once a week. Ten days after sowing, thinning was performed, leaving one plant per cup at a height of three centimeters.

TABLE 1. Hoagland nutrient solution.

Element	Concentration (mg/L)	Element	Concentration (mg/L)
N	210.1	Cu	0.02
P	31.0	Cl	0.64
K	234.6	Fe	5.0
Ca	200.4	Mn	0.5
Mg	48.6	Mo	0.01
S	64.2	Zn	0.05
B	0.5		

Five treatments were tested, consisting of different illumination levels used in seedling development: 0 (control), 25, 50, 75, and 100  $\mu\text{mol m}^{-2} \text{s}^{-1}$ . Lighting was provided using LED lamps composed of blue and red LEDs (20% blue and 80% red). The photoperiod was 16 h of light and 8 h of darkness, and the average room temperature was 28 °C. The experimental design was completely randomized using 20 replicates per treatment, and the experimental unit consisted of a pot with one plant.

The seedlings were cultivated for 36 days after sowing; at the end of the experiment, the following variables were evaluated: plant height (mm), number of

leaves, stem diameter (mm), internode number, shoot fresh weight (g), and root fresh weight (g). The plant height and stem diameter were measured using a ruler and a digital caliper, respectively. The shoot and root fresh weights were determined after the seedlings were removed from the containers, washed, dried with paper towels, and the roots were separated from the shoots.

The data obtained were analyzed for variance and the means were compared using Duncan's test. The data for the variable number of leaves were transformed into the square root of  $(x+0.5)$ . A 5% probability level was used for statistical analysis and the results are listed in Table 2.

TABLE 2. Data obtained at the end of the experiment.

Variables	Light intensity ( $\mu\text{mol m}^{-2} \text{s}^{-2}$ )				
	0	25	50	75	100
Plant height (mm)	161 a*	144 ab	126 b	146 ab	86 c
Number of leaves	7.5 b	7.0 b	6.8 b	8.8 a	6.6 b
Stem diameter (mm)	3.5 b	3.6 ab	3.3 b	4.0 a	3.4 b
Number of internodes	3.3 b	3.1 b	3.5 b	4.5 a	3.3 b
Shoot fresh weight (g)	3.4 ab	3.2 b	3.2 b	4.1 a	2.0 c
Root fresh weight (g)	1.6 c	2.2 bc	3.4 ab	4.0 a	2.1 c

\* Means followed by the same letter do not differ statistically at a 5% probability level.

### Development of the fuzzy models

Based on the data obtained in the experiment conducted by Rocha et al. (2014), fuzzy models were developed to understand the effects of the different supplemental lighting levels on the development of bell pepper seedlings. All models were developed using MATLAB® Fuzzy Toolbox® platform. Mandani's inference method (Mandani, 1976), used in several studies (Lin et al., 2013; Bedoya et al., 2015; Schiassi et al., 2015), was adopted to define logical connectives used in establishing the rule bases.

The rules were defined in the form of linguistic sentences based on experimentally collected data and the

assistance of four experts in fuzzy modeling and agricultural production. The methodology proposed by Cornelissen et al. (2002) and employed by Yanagi Junior et al. (2012) and Lourençoni et al. (2019) was applied to choose the experts.

Based on the input variables and experimental data, the fuzzy model was used to predict the output variables: plant height (mm), number of leaves, stem diameter (mm), internode number, shoot fresh weight (g), and root fresh weight (g).

The observed (O) and predicted (P) values for each variable were graphically compared using scatter diagrams. In each scatterplot, the straight line  $O = P$  represents the optimal prediction. A line determined by a linear fit between O and P was included with the intercept and angular

coefficient to observe the general behavior of the forecasts and their deviations from the ideal forecast ( $O = P$ ).

Using the developed fuzzy models, the plant height (mm), number of leaves, stem diameter (mm), internode number, shoot fresh weight (g), and root fresh weight (g) were simulated, and the results were validated using the experimentally collected data through the error rate: mean error (ME)/trend/BIAS, also called systematic error (Equation 1); mean absolute error (MAE) (Equation 2); mean square error (MSE) (Equation 3); root MSE (RMSE) (Equation 4); mean absolute percentage error (MAPE) (equation 5); and the Nash–Sutcliffe efficiency index (NSE) (Nash and Sutcliffe, 1970) (Equation 6), calculated using the following equations:

$$ME = Bias = \frac{1}{n} \sum_{i=1}^n (P_i - O_i) \quad (1)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |P_i - O_i| \quad (2)$$

$$MSE = \frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (4)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{O_i - P_i}{O_i} \right| \cdot 100 \quad (5)$$

$$NSE = 1 - \left[ \frac{\sum_{i=1}^n (P_i - O_i)^2}{\sum_{i=1}^n (O_i - \bar{O})^2} \right] \quad (6)$$

where:

$P_i$  and  $O_i$  are the  $i$ th predicted and observed values (%), respectively;

$n$  is the total number of samples, and

$\bar{O}$  is the mean of the observed values (%).

## RESULTS AND DISCUSSION

The lighting level data applied in the experiment was used as input variable to the fuzzy model that best fit the data, represented by triangular pertinence curves (Figure 1), which were chosen to better reproduce the dataset (Schiassi et al., 2015; Lourençoni et al., 2019).

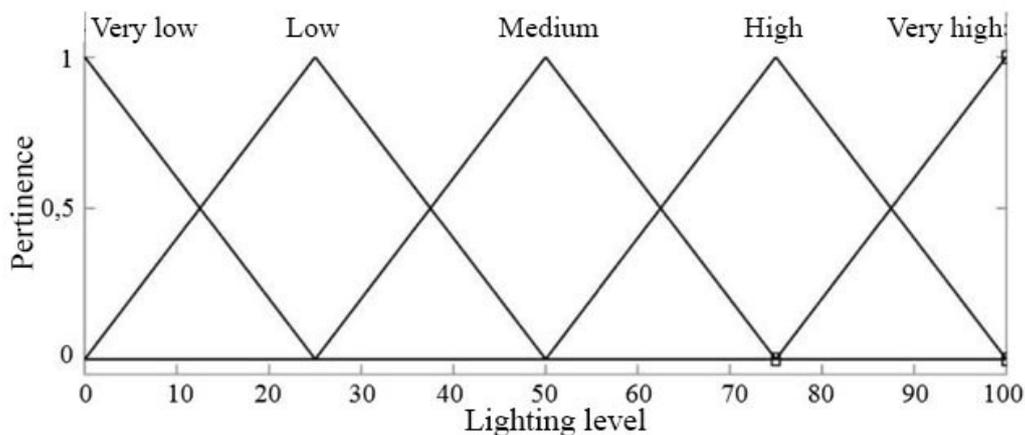


FIGURE 1. Pertinence functions for the input variable (lighting level).

Based on the input variables, the model was used to predict the following output variables: plant height (mm), number of leaves, stem diameter (mm), internode number, shoot fresh weight (g), and root fresh weight (g) (Figure 2). All the output variables were represented by triangular pertinence curves, with their mean delimiter defined as the value found in the experiment.

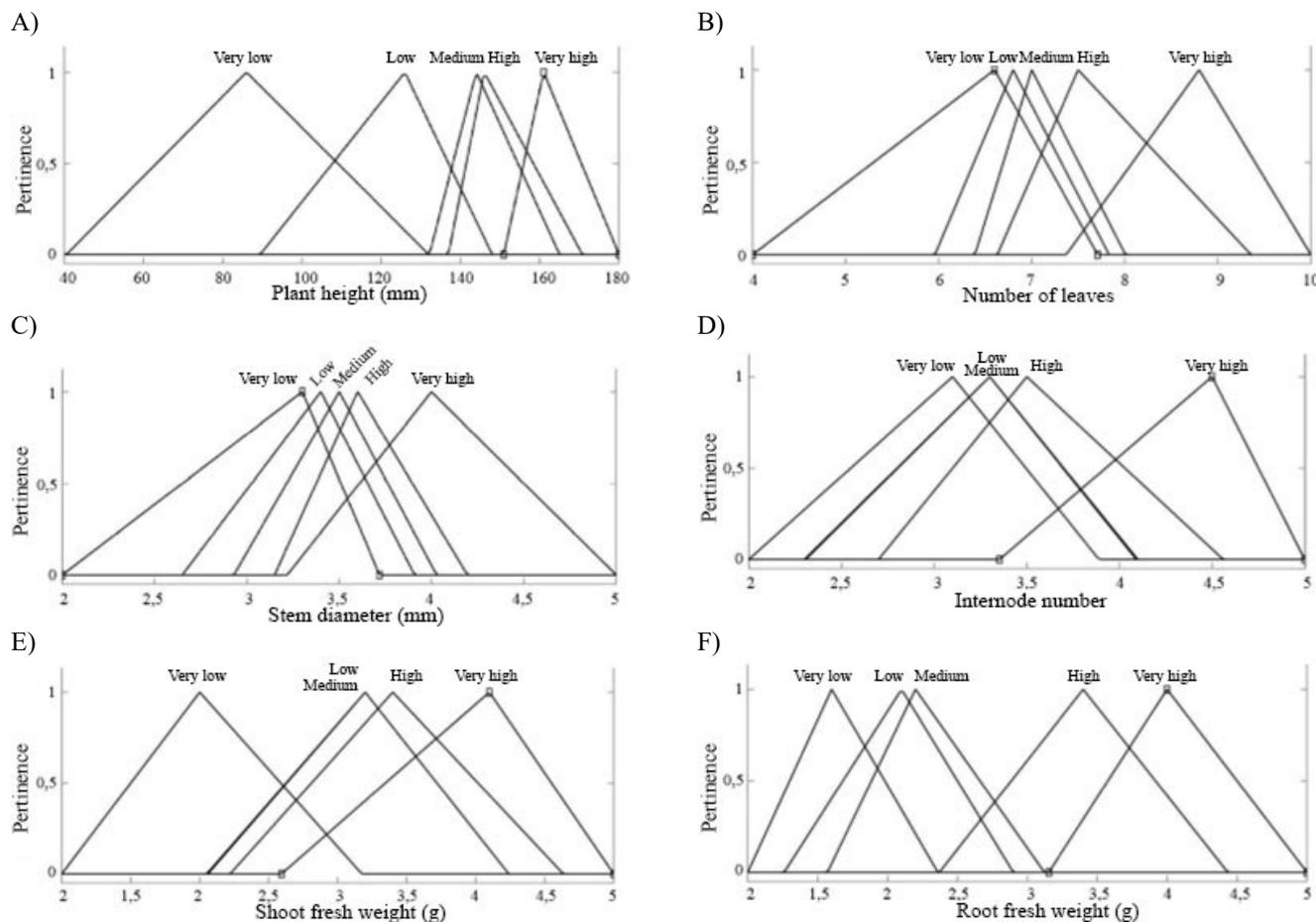


FIGURE 2. Pertinence functions for the output variables: (A) plant height, (B) number of leaves, (C) stem diameter, (D) internode number, (E) shoot fresh weight, and (F) root fresh weight.

By combining the input and output variables obtained in the experiment with the experience of the four experts on fuzzy modeling and agricultural production (Cornelissen et al., 2002), five rules were defined (Table 3), and a weighting factor equal to 1 was adopted for all rules because they all have the same importance in determining the model responses.

TABLE 3. Rule set for the fuzzy model.

Rule	Input variable			Output variables			
	Supplemental lighting level	Plant height	Number of leaves	Stem diameter	Internode number	Shoot fresh weight	Root fresh weight
1	Very low	Very high	High	Medium	Low	High	Very low
2	Low	Medium	Medium	High	Very low	Low	Medium
3	Medium	Low	Low	Very low	High	Low	High
4	High	High	Very high	Very high	Very high	Very high	Very high
5	Very high	Very low	Very low	Low	Low	Very low	Low

Defuzzification was performed using the center of gravity method (centroid or center of area), which considers all output alternatives and converts the fuzzy set obtained by inference into a numerical value (Leite et al., 2010; Schiassi et al., 2015; Lourençoni et al., 2019).

After defining the model rules, two-dimensional graphs were obtained for each output variable (Figure 3). In general, the graphs indicate that an intensity of  $75 \mu\text{mol m}^{-2} \text{s}^{-1}$  resulted in the best results, excluding those for plant height. This result is in agreement with the findings of Rocha et al. (2014).

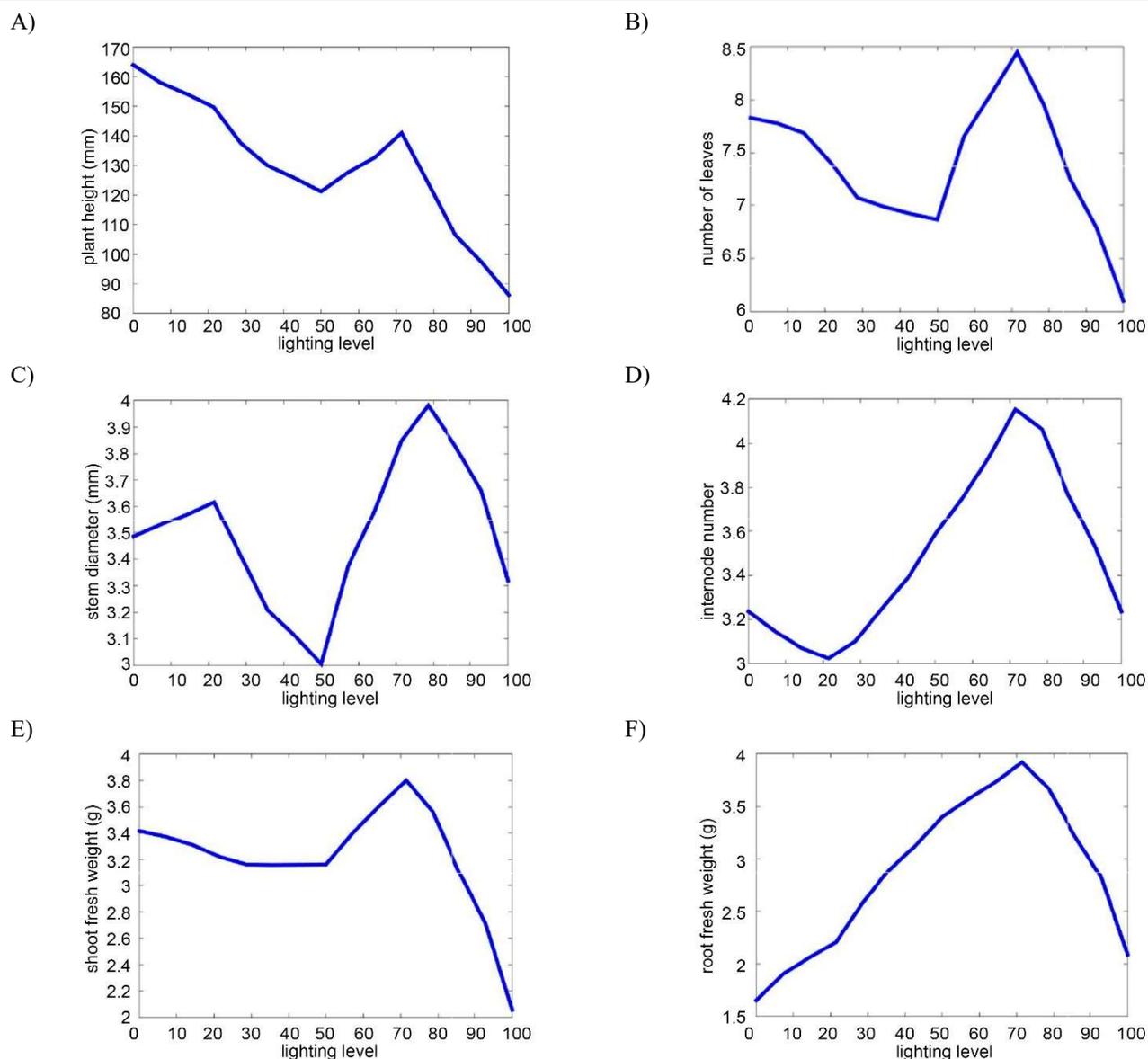


FIGURE 3. Graphs of output variables: (A) plant height, (B) number of leaves, (C) stem diameter, (D) internode number, (E) shoot fresh weight, and (F) root fresh weight.

We determined the statistical indices for the adequacy and precision of the model with respect to the responses of the variables analyzed (Table 4). The mean error (ME or BIAS) indicated that the difference in the results predicted by the model was lower for the calculated

variables (bias between -0.071 and 0.037), with a higher value only for the plant height (1.324). Values close to those found by Lins et al. (2021 a), who developed a fuzzy model for predicting the eye and crest temperatures of laying hens, obtained bias values of 0.0003 and 0.0019, respectively.

TABLE 4. Model error rates: ME or BIAS, MAE, MSE, RMSE, MAPE, and NSE.

	ME=BIAS	MAE	MSE	RMSE	MAPE	NSE
Plant height	1.324	3.267	13.901	132.6	2.329	0.978
Number of leaves	-0.009	0.219	0.076	0.276	3.122	0.878
Stem diameter	-0.053	0.101	0.02	0.141	2.963	0.659
Internode number	-0.071	0.106	0.014	0.12	2.886	0.941
Shoot fresh weight	-0.038	0.069	0.009	0.096	2.097	0.98
Root fresh weight	0.037	0.043	0.003	0.054	1.939	0.996

The MAE, MSE, and RMSE values represent the dispersion in the observed and predicted values. In all variables, except for the seedling height, the values of these indicators were close to zero, which represents a low dispersion of the model. Values between 1.93% and 3.13% for all variables were obtained for the MAPE, which indicates the accuracy of the model. These values were lower than those obtained by Lins et al. (2021a), which were 2.90% and 6.30% for the fuzzy model to predict the eye and crest temperatures of laying hens, respectively.

In contrast, the NSE was close to 1 for the shoot and root fresh weight, internode number, and plant height variables, and was slightly lower for the number of leaves and stem diameter. The NSE indicates the predictive ability of the model, where values closer to 1 indicate better performance.

From the scatter plots (Figure 4), the developed fuzzy model could predict all variables with a good efficiency, and the correlations ranged from 0.90 to 0.99. Therefore, the model can be used to predict the agronomic parameters of bell pepper seedlings under different light intensities.

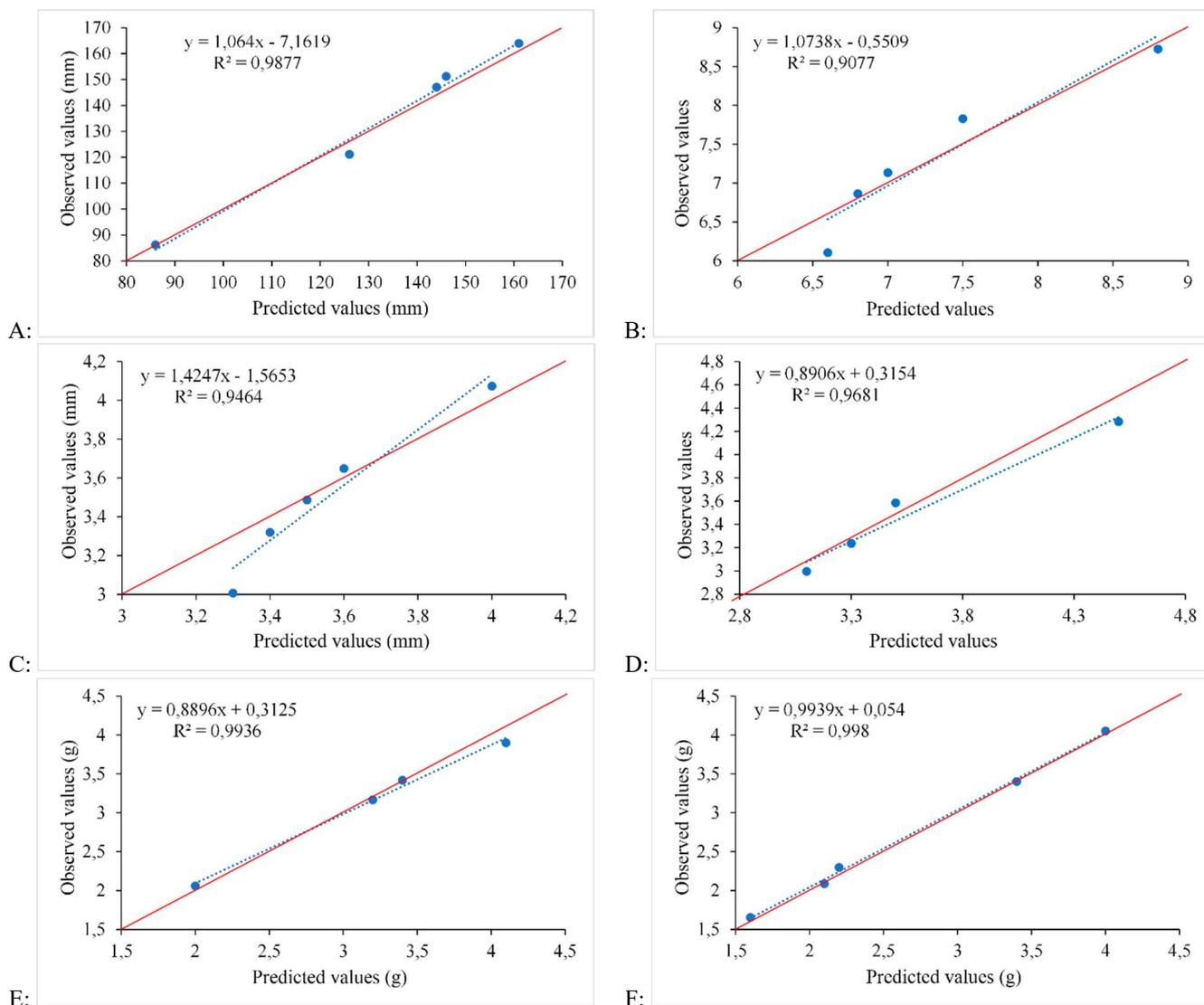


FIGURE 4. Scatter diagrams for (A) plant height, (B) number of leaves, (C) stem diameter, (D) internode number, (E) shoot fresh weight, and (F) root fresh weight.

The results indicated that this inference system can be useful for developing controllers for the automatic management of supplemental lighting in bell pepper seedling production, and can also be applied to other vegetables.

**CONCLUSIONS**

The proposed fuzzy model allowed the efficient estimation of agronomic parameters of bell pepper seedlings under different light intensities, thus enhancing decision making for the efficient control of supplemental lighting in the cultivation of bell pepper seedlings.

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**REFERENCES**

Bedoya ODM, Junior TY, Pires MFA, Lopes MA, Lima RR (2015) Fuzzy system to predict physiological responses of Holstein cows in southeastern Brazil. *Revista Colombiana de Ciências Pecuárias* 28(1):42-53.

Bezerra FC (2003) *Produção de mudas de hortaliças em ambiente protegido*. Fortaleza, Embrapa Agroindústria Tropical. 22 p.

- Claypool NB, Lieth JH (2020) Physiological responses of pepper seedlings to various ratios of blue, green, and red light using LED lamps. *Scientia Horticulturae* 268:109371. DOI: <http://dx.doi.org/10.1016/j.scienta.2020.109371>.
- Cornelissen AMG, Van den berg J, Koops WJ, Kaymak U (2002) Elicitation of expert knowledge for fuzzy evaluation of agricultural production systems. *Agriculture, Ecosystems & Environment* 95(1):1–18.
- Díaz-Galián MV, Torres M, Sanchez-Pagán JD, Navarro PJ, Weiss J, Egea-Cortines M (2021) Enhancement of strawberry production and fruit quality by blue and red LED lights in research and commercial greenhouses. *South African Journal of Botany* 140:269–275. DOI: <http://dx.doi.org/10.1016/j.sajb.2020.05.004>.
- Gabriel Filho LRA, Silva AO, Cremasco CP, Putti FF (2022) Fuzzy modeling of the effect of irrigation depths on beet cultivars. *Engenharia Agrícola* 42(1): e20210084. DOI: <http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v42n1e20210084/2022>
- Hoagland DR, Arnon DI (1950) The water-culture method for growing plants without soil. California Agricultural Experiment Station. Circular 347.
- Joshi NC, Ratner K, Eidelman O, Bednarczyk D, Zur N, Many Y, Shahak Y, Aviv-Sharon E, Achiam M, Gilad Z, Charuvi D (2019) Effects of daytime intra-canopy LED illumination on photosynthesis and productivity of bell pepper grown in protected cultivation. *Scientia Horticulturae* 250: 81–88. DOI: [10.1016/j.scienta.2019.02.039](https://doi.org/10.1016/j.scienta.2019.02.039)
- Koksal N, Incesu M, Teke A (2015) Supplemental LED lighting increases pansy growth. *Horticultura Brasileira* 33(4):428–433. DOI: <http://dx.doi.org/10.1590/s0102-053620150000400004>.
- Leite MS, Fileti AMF, Silva FV (2010) Desenvolvimento e aplicação experimental de controladores fuzzy e convencional em um bioprocesso. *Revista Controle & Automação* 21(2):147–158.
- Lin CS, Yeh PT, Chen DC, Chiou YC, Lee CH (2013) The identification and filtering of fertilized eggs with a thermal imaging system. *Computers and Electronics in Agriculture* 91:94–105.
- Lins ACSS, Lourençoni D, Júnior TY, Miranda IB, Santos IEA (2021 a) Neuro-fuzzy modeling of eyeball and crest temperatures in egg-laying hens. *Engenharia Agrícola* 41(1):34–38. DOI: <http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v41n1p34-38/2021>
- Lins ACSS, Souza IJS, Lourençoni D, Yanagi Júnior T, Santos IEA (2021 b) Fuzzy logic modeling of the ocular temperature of cattle in thermal stress conditions. *Engenharia Agrícola* 41(4):418–426. DOI: <http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v41n4p418-426/2021>
- Lourençoni D, Yanagi Junior T, Abreu PG, Campos AT, Yanagi SNM (2019) Productive responses from broiler chickens raised in different commercial production systems – part I: Fuzzy modeling. *Engenharia Agrícola* 39(1):1–10.
- Mandani EH (1976) Advances in the linguistic syntesis of fuzzy controllers. *International Journal of Man-Machine Studies* 8(6):669–678.
- Paucek I, Pennisi G, Pistillo A, Appolloni E, Crepaldi A, Calegari B, Spinelli F, Cellini A, Gabarrell X, Orsini F, Gianquinto G (2020) Supplementary LED interlighting improves yield and precocity of greenhouse tomatoes in the mediterranean. *Agronomy* 10(7):1002. DOI: <http://dx.doi.org/10.3390/agronomy10071002>.
- Putti FF, Cremasco CP, Silva Junior JF, Gabriel Filho LRA (2022) Fuzzy modeling of salinity effects on radish yield under reuse water irrigation. *Engenharia Agrícola* 42(1): e215144. DOI: <http://dx.doi.org/10.1590/1809-4430-Eng.Agric.v42n1e215144/2022>
- Rahman MH, Azad MOK, Islam MJ, Rana MS, Li KH, Lim YS (2021) Production of potato (*Solanum tuberosum* L.) seed tuber under artificial led light irradiation in plant factory. *Plants* 10 (2):1–17. DOI: [10.3390/plants10020297](https://doi.org/10.3390/plants10020297).
- Rocha PSG, Santos AC, Menegatti PWS, Amaral AS, Rodrigues APC (2014) Produção de mudas de pimentão sob diferentes intensidades luminosas com LED's. In: Congresso Brasileiro de Olericultura. Palmas, Associação Brasileira de Horticultura.
- Santos HCA, Junior JAL, Silva ALP, Castro GLS, Gomes RF (2020) Yield of fertigated bell pepper under different soil water tensions and nitrogen fertilization. *Revista Caatinga* 33(1):172–183
- Schiassi L, Junior TY, Ferraz PFP, Campos AT, Silva GR, Abreu LHP (2015) Comportamento de frangos de corte submetidos a diferentes ambientes térmicos. *Engenharia Agrícola* 35(3):390–396.
- Tomasiello S, Alijani Z (2021) Fuzzy-based approaches for agri-food supply chains: a mini-review. *Soft Computing* 25(11): 7479–7492. DOI: <https://doi.org/10.1007/s00500-021-05707-3>
- Yanagi Junior T, Schiassi L, Abreu LHP, Barbosa JA, Campos AT (2012) Procedimento fuzzy aplicado à avaliação da insalubridade em atividades agrícolas. *Engenharia Agrícola* 32(3):423–434.