Identification of the best treatment combination for seedling production through fuzzy logic model and Pareto dominance criterion

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Abstract: The present study consists of the development of a fuzzy logic model for categorizing seedlings produced using various combination of potting mix and pot volume and identification of the best combination of treatment for the large scale production of seedlings for mechanical transplanting using Pareto dominance criterion. A fuzzy logic model with simple expert system rules was developed to categorize the seedlings based on its dry weight of root and shoot biomasses. The suitable membership function for the model was selected by picking up the shape of the membership function from the list of families and fine tuning the values of parameters of the function. The model assigned a rational value called biomass growth index (BGI) between 0 and 10 to the seedling such that the seedling with higher growth of both root and shoot biomasses was assigned higher value of BGI and vice versa. The categorization ability of the developed model was found to be reasonably good and it could be used for the evaluation of growth of seedlings produced from various treatments just prior to transplanting. The best combination of potting mix and pot volume for the large scale production of seedlings was identified considering BGI of the seedlings, the cost of preparation of pots, and the weight of pot using Pareto dominance criterion. Among the set of non-dominated solutions, paper pots of 50 cm^3 volume filled with mix of 25% vermicompost and 75% sand and soil in equal proportion by volume was selected for the large scale production of the seedlings of tomato, eggplant, and chili peppers. The proposed fuzzy logic model is very easy to develop and when it is coupled with Pareto dominance criterion, it can be effectively used in the decision support system for the identification of the best combination of treatment for the seedling production.

Keywords: Fuzzy logic model, membership function, Pareto dominance, root:shoot ratio, biomass growth

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1 Introduction

Initial growth stage of vegetable seedlings is critical for good production. Research directions have focused on ways to produce seedlings that meet mechanization requirements, survive field establishment, and contribute to plant health that could affect the yield of plants developed from seedlings (Koller et al., 2004; Nicola et al., 2004; Singh et al., 2005; Russo, 2006). In many scientific investigations, effect of treatments on seedlings is studied in terms of its growth and yield potential. Besides the factors of the growth and the yield potential of seedlings, expanding interest towards the growth of seedlings for transplanting by mechanical means necessitates the decision to be taken considering multiple factors viz., cost, weight of mix, space requirement, energy requirement, etc. Hence, there is a genuine need to distinguish the effect of each treatment from the other so that the one which suits best from all considerations can be selected for the large scale production of seedlings.

The dry weight of seedlings has been used for the comparison of the growth of seedlings produced from various treatments. Furthermore, the growth potential of the vegetable seedling has been reported to be directly

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proportional to its dry weight (Nicola and Basoccu, 1994; Brewster, 2008; Gupta et al., 2010). The dry weight of seedling includes the weight of both above and below ground portion of seedling. For the growth and development of healthy plants, balanced growth of root and shoot systems are essential (Nicola, 1998). The root:shoot ratio is most commonly used to express the balanced growth of seedlings. Zandstra and Liptay (1999) opined that the high root:shoot ratios are important to ensure the cohesion of the plugs during transplanting and to ensure good take-off after transplanting. However, the root:shoot ratio is a simple ratio of the dry weight of root and shoot biomasses. The root:shoot ratio does not represent the morphology of seedlings correctly (Kumar and Raheman, 2010). This is due to the fact that the seedling with a well grown root and shoot biomasses may have the same root:shoot ratio as that of the seedling with stunted growth. In order to overcome this, the root:shoot ratio is generally corrected for the height or the dry weight of the seedling to be a good measure of plant survival particularly in the case of perennials (Ledig et al., 1970; Carlson and Preisig, 1981). In most of the literature related to vegetable seedlings, dry weights of root biomass and shoot biomass of seedlings are studied separately.

The main and interaction effects of the treatment on biomass growth of vegetable seedlings seldom exhibit continuous component to model it by regression equations. Hence, biomass growth data are plotted and differences between them for various treatments are compared. The approach followed in this paper for the comparison of biomass growth of seedlings subjected to various treatments is based on the fuzzy logic model. The proposed technique assigns a rational value between 0 and 10 to the seedling based on its dry weight of root and shoot biomasses. Fuzzy logic can effectively translate the experience of a horticulturist or gardener into a set of expert system rules (Center and Verma, 1998; Huang et al., 2010). For example, a horticulturist often uses the terms such as poor or good to assess the quality of seedlings. However, these terms do not constitute a well-defined boundary. Further, a gardener may know the approximate interaction between biomass growth of seedlings and their growth and yield potential from his knowledge and experience. For example, the larger the root and shoot biomass, the better the growth and survival after the field establishment and the yield. Therefore, it is quite possible to devise a fuzzy logic model to predict the growth of the seedling in terms of a rational value between 0 and 10 from the given values of its dry weight of root and shoot biomasses.

The present work consists of the following:

1) Development of a fuzzy logic model to categorize the seedlings subjected to various treatments.

2) Use of the developed model along with other factors for the identification of the best combination of treatments for the large scale production of seedlings.

2 Theoretical considerations

2.1 General procedure for the development of a fuzzy logic model

Creation of fuzzy sets: In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to define uncertainty of classes that do not have clearly-defined boundaries. For each input and output variable, fuzzy sets are created by dividing the universe of discourse into a number of sub-regions, named in linguistic terms (high, medium, low, etc.). If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A in X is defined as a set of ordered pairs as:

$$A=\{x,\ \mu_A(x)\ |\ x\in X\}$$

where, $\mu_A(x)$ is the membership function of x in A.

Membership functions and fuzzification: Once the fuzzy sets are chosen, a membership function (MF) for each set should be created. A MF is a typical curve that converts the numerical value of input within a range from 0 to 1, indicating the belongingness of the input to a fuzzy set. This step is known as fuzzification. MF can have various forms, such as triangle, trapezoid, Gaussian, bell, sigmoid, S-shaped, etc. (Zhao and Bose, 2002; Majumdar and Ghosh, 2008). The details of the MF are given in Section 2.2.

Fuzzy linguistic rules: Fuzzy linguistic rules provide quantitative reasoning that relates input fuzzy sets with output fuzzy sets. A fuzzy rule base consists of a number of fuzzy 'if-then' rules. For example, in the case of two-input and single-output fuzzy system, it can be expressed as " If x is high and y is low then z is good", where x and y are the variables representing two input, and z is the variable representing the output. High, low, and good are the fuzzy sets of x, y, and z, respectively.

Defuzzification: The output of each rule is also a fuzzy set. Output fuzzy sets are then aggregated into a single fuzzy set. This step is known as aggregation. Finally, the resulting set is resolved to a single crisp number by defuzzification. There are several methods of defuzzification like centroid, centre of sums, mean of maxima, and left-right maxima. However, centroid of area method of defuzzification is generally used in most of the cases and it is done as shown below:

$$x* = \frac{\int \mu_A(x)\,x\,dx}{\int \mu_A(x)\,dx}$$

where, $x*$ is the defuzzified output and $\mu_A(x)$ is the output fuzzy set after aggregation of individual implication results.

2.2 Fuzzy MFs

MF characterizes the fuzziness in a fuzzy set. A MF can have different shapes as shown in Figure 1. The general classification of MF is as follows.

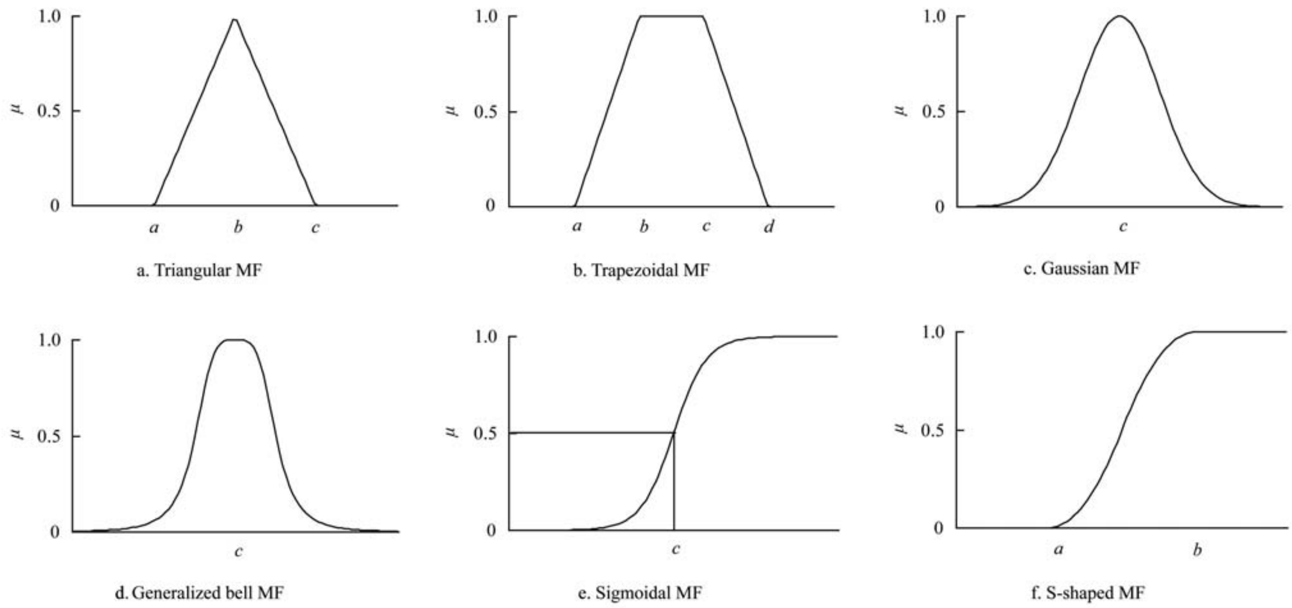

Figure 1 Various MFs

2.2.1 Piecewise linear functions

Piecewise linear functions constitute the simplest type of MF, and they may be either triangular or trapezoidal type. A triangular MF (Figure 1(a)) is specified by three parameters (a, b, and c) as follows:

$$f(x;\, a,b,c) = \max\left\{ \min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right\}$$

The parameters (a, b, and c with $a < b < c$) determine the x coordinates of the 3 corners of the underlying triangular MF.

A trapezoidal MF (Figure 1(b)) is specified by four parameters (a, b, c, and d) as follows:

$$f(x;\, a,b,c,d) = \max\left\{ \min\left(\frac{x-a}{b-a}, 1, \frac{c-x}{c-b} \right), 0 \right\}$$

The parameters (a, b, c, and d with $a < b \leq c < d$) determine the x coordinates of the 4 corners of the underlying trapezoidal MF.

2.2.2 Gaussian function

A Gaussian MF (Figure 1(c)) is specified by two parameters (c and σ) as follows:

$$f(x;\, c,\sigma) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)2}$$

The parameters c represents the centre and σ determines the width of MF.

2.2.3 Bell-shaped function

A generalized bell MF (or bell MF) (Figure 1(d)) is specified by three parameters (a, b, and c) as follows:

$$f(x;\ a,b,c)=\frac{1}{1+\left|\dfrac{x-c}{a}\right|^{2b}}$$

where the parameter b is usually positive. The parameter c represents the centre, a determines the width, and b controls the steepness of the MF (slope at the crossover points).

2.2.4 Sigmoidal function

A sigmoidal MF (Figure 1(e)) is defined by

$$f(x;\ a,\ c)=\frac{1}{1+e^{-a(x-c)}}$$

where, a controls the slope at the crossover point $x = c$.

2.2.5 Polynomial based function

Three polynomial based MFs in this family are defined as polynomial-Z (zmf), polynomial-S (smf), and polynomial-PI (pimf). They are named according to their shapes. Only smf is considered in the present study. Its shape is like S (Figure 1(f)) and is given by

$$y = \text{smf}\ (x, [a, b])$$

where, a and b represent the extremes of the sloped portion of the curve.

3 Materials and methods

3.1 Data for the development of model

Data on the dry weight of root and shoot biomasses of the seedlings of tomato (*Solanum lycopersicum*), eggplant (*Solanum melongena*), and chili peppers (*Capsicum frutenscens*) at the end of the seedling stage (Kumar and Raheman, 2010) were used for the development of the fuzzy logic model. Seedlings were grown in paper pots filled with soil based potting mix amended with vermicompost. The purpose of the experiment was to identify the best combination of proportion of vermicompost in potting mix and pot volume that meet the requirements of growing them for mechanical transplanting.

Soil and sand were mixed in equal proportion and vermicompost was added to the mix at 20%, 25%, 33.33%, and 50% by volume to prepare four mixes (designated as M1, M2, M3, and M4, respectively). One more mix (designated as M5) was prepared with 50% soil (without sand) and 50% vermicompost by volume. Double layered cubical paper pots of 50 cm^3 (36.8 mm sides), 65 cm^3 (40.2 mm sides), 80 cm^3 (43.1 mm sides), and 100 cm^3 (46.4 mm sides) volume (designated as V1, V2, V3, and V4, respectively) were used. Dependent parameters were average values (10 replications) of the dry weight of root and shoot biomasses of the seedlings and they are presented in Table 1. The dry weight values of the tomato seedlings were used for the model development, whereas those of eggplant and chili peppers were used for the validation of the model.

Table 1 Mean values of dry weight (in grams) of root and shoot biomasses of seedlings just prior to transplanting

Mix	Pot volume	Treatment designation	Tomato		Eggplant		Chili peppers	
			Root	Shoot	Root	Shoot	Root	Shoot
M1	V1	T1	0.011	0.092	0.017	0.075	0.014	0.049
	V2	T2	0.020	0.110	0.024	0.107	0.013	0.052
	V3	T3	0.021	0.103	0.034	0.157	0.013	0.039
	V4	T4	0.021	0.099	0.029	0.137	0.015	0.063
M2	V1	T5	0.021	0.112	0.029	0.163	0.018	0.079
	V2	T6	0.019	0.128	0.022	0.122	0.015	0.071
	V3	T7	0.024	0.108	0.028	0.145	0.015	0.078
	V4	T8	0.023	0.089	0.034	0.151	0.016	0.074
M3	V1	T9	0.021	0.104	0.032	0.132	0.015	0.070
	V2	T10	0.019	0.108	0.028	0.130	0.014	0.089
	V3	T11	0.018	0.103	0.019	0.112	0.017	0.094
	V4	T12	0.018	0.079	0.028	0.142	0.012	0.078
M4	V1	T13	0.022	0.114	0.021	0.128	0.011	0.040
	V2	T14	0.019	0.106	0.030	0.169	0.013	0.078
	V3	T15	0.019	0.104	0.023	0.130	0.014	0.098
	V4	T16	0.019	0.113	0.032	0.180	0.016	0.081
M5	V1	T17	0.010	0.046	0.015	0.093	0.008	0.038
	V2	T18	0.008	0.049	0.018	0.106	0.011	0.054
	V3	T19	0.008	0.058	0.027	0.124	0.011	0.063
	V4	T20	0.004	0.025	0.023	0.115	0.010	0.054

The best combination of proportion of vermicompost in soil based potting mix and pot volume for the production of paper pot seedlings for mechanical transplanting was determined for the selected varieties of tomato, eggplant, and chili peppers considering the growth of seedlings, the cost of preparation of paper pots, and the weight of pot (before sowing seeds into it).

3.2 Development of fuzzy logic model

The purpose of the fuzzy logic model is to categorize the seedlings by assigning a rational value called biomass growth index (BGI) between 0 and 10 based on its root and shoot biomass growth at the end of seedling stage. The higher the BGI for the seedling, the better its growth and yield potential. The mean values of the dry weight of root biomass and the dry weight of shoot biomass of the seedlings just prior to transplanting were used as the input parameters to the fuzzy logic model. The output parameter of the model was BGI. A MATLAB (version 7.0) (Mathworks Inc., New York, USA) based coding was used to execute the proposed fuzzy logic model to evaluate the seedling growth and quality.

The first step in the development of the fuzzy logic model is the fuzzification of input parameters using appropriate MF. The entire range of values of the dry weight of the root and shoot biomasses were divided separately into two equally spaced linguistic fuzzy sets as ‘high’ and ‘low’ values. The two fuzzy sets for each of the input parameters covered the whole input spaces.

Theoretically there could be 2×2 = 4 fuzzy rules, as there are two input variables and each one of them are having two linguistic levels. As output of the fuzzy rule is a fuzzy set, four output fuzzy sets, ‘poor’, ‘moderate’, ‘good’, and ‘very good’ were used to describe the biomass growth of seedlings in terms of BGI from 0 to 10. All six forms of MFs (Section 2.2) were tried for input as well as for the output. Figure 2 depict the sigmoidal MF plots for the dry weight of root and shoot biomasses and BGI for the tomato seedlings.

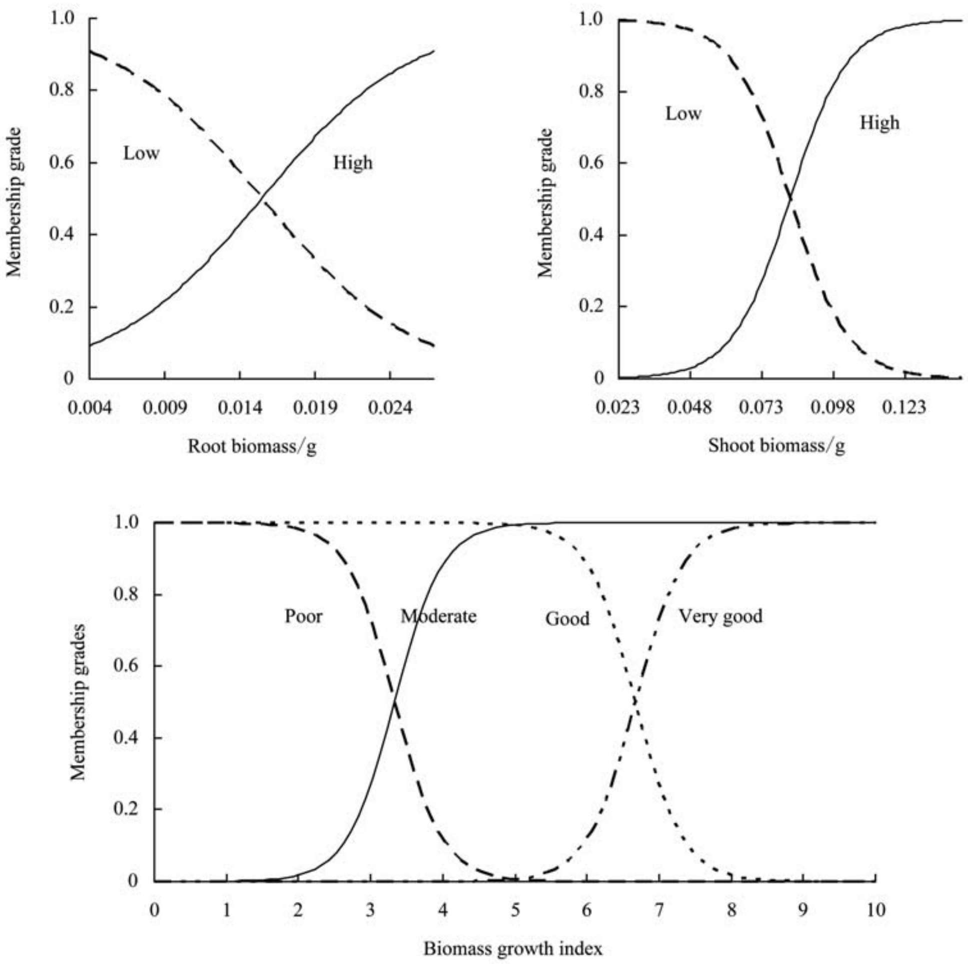

Figure 2 Sigmoidal MF plots of root biomass, shoot biomass and BGI

Four fuzzy rules were developed based on expert knowledge viz., the larger the root and shoot biomasses, the better the growth and survival after field establishment and yield (Nicola and Basoccu, 1994; Brewster, 2008), and a large top requires a large root system to supply water and nutrients to it (Leskovar and Stoffella, 1995). The fuzzy rules are shown in Figure 3.

Here 'min' function was used to represent 'fuzzy and' operator and 'max' function was used to represent 'fuzzy or' operator between two fuzzy sets *A* and *B* as shown below:

$$fuzzy\ and = \min\{\mu_A(x), \mu_B(x)\}$$

$$fuzzy\ or = \max\{\mu_A(x), \mu_B(x)\}$$

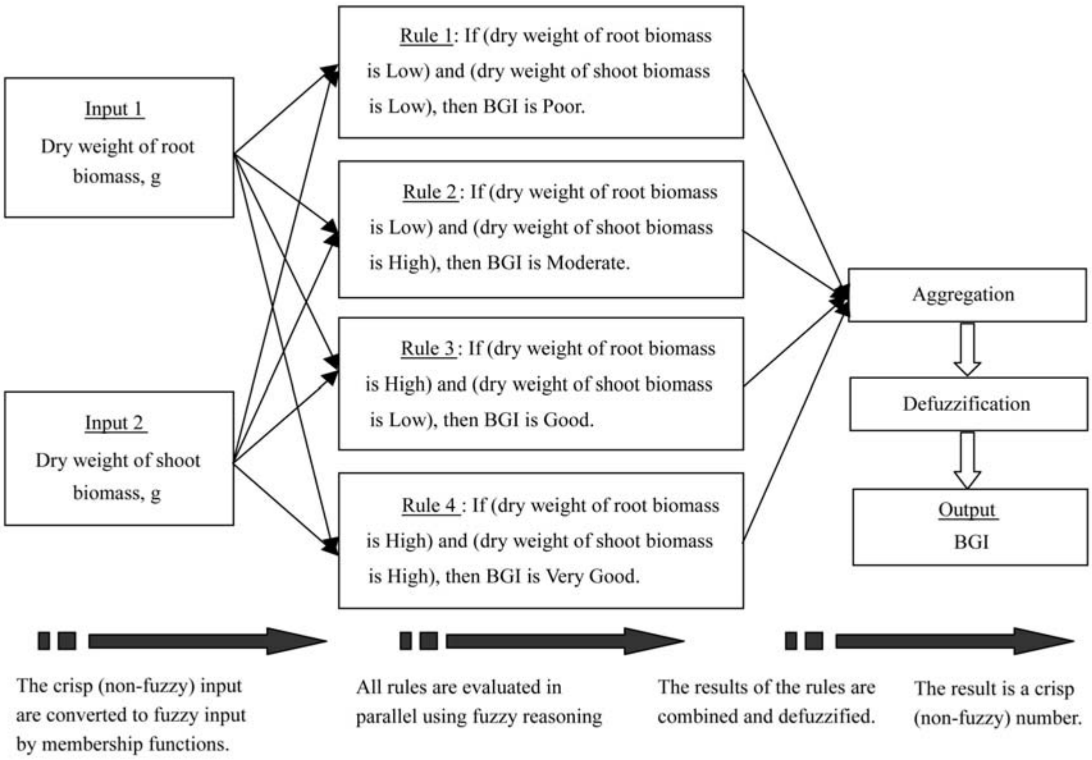

Figure 3 Schematic representation of fuzzy logic model of seedling growth

3.3 Operation of fuzzy logic model

Figure 4 schematically demonstrates the operation of the developed fuzzy logic model with sigmoidal MF with an example. All four fuzzy rules have been depicted in the diagram. According to the fourth rule, if values of the dry weight of root and shoot biomasses are 'high', then BGI will be 'very good'. For example, if the dry weight of root biomass and shoot biomass is 0.024 and 0.108 g respectively, then all four fuzzy rules are evaluated simultaneously to determine the BGI. As 'fuzzy and' function has been used in the antecedent part of the fuzzy rules, the minimum value of the MF was considered to produce the output fuzzy set of each fuzzy rule. Outputs of active fuzzy rules were then aggregated to get a final output fuzzy set. As 'fuzzy or' function has been used in the consequent part of the fuzzy rules, the maximum area under the output MF curve was considered for the aggregation of the rules to get a final output fuzzy set. The final output fuzzy set was defuzzified using centroid of area method to produce the crisp output (BGI) of 7.51 as shown in Figure 4.

Fuzzy rules determine the input-output relationship of the model. The surface plot shown in Figure 5 depicts the effect of the root and shoots biomasses of the tomato seedlings on BGI for sigmoidal MF. As the dry weight of root and shoot biomass increases, there is an increase in BGI as expected. Further, different MFs gave different value of BGI to the same set of input parameters. This is due to the characteristics of the MF used for the development of the model.

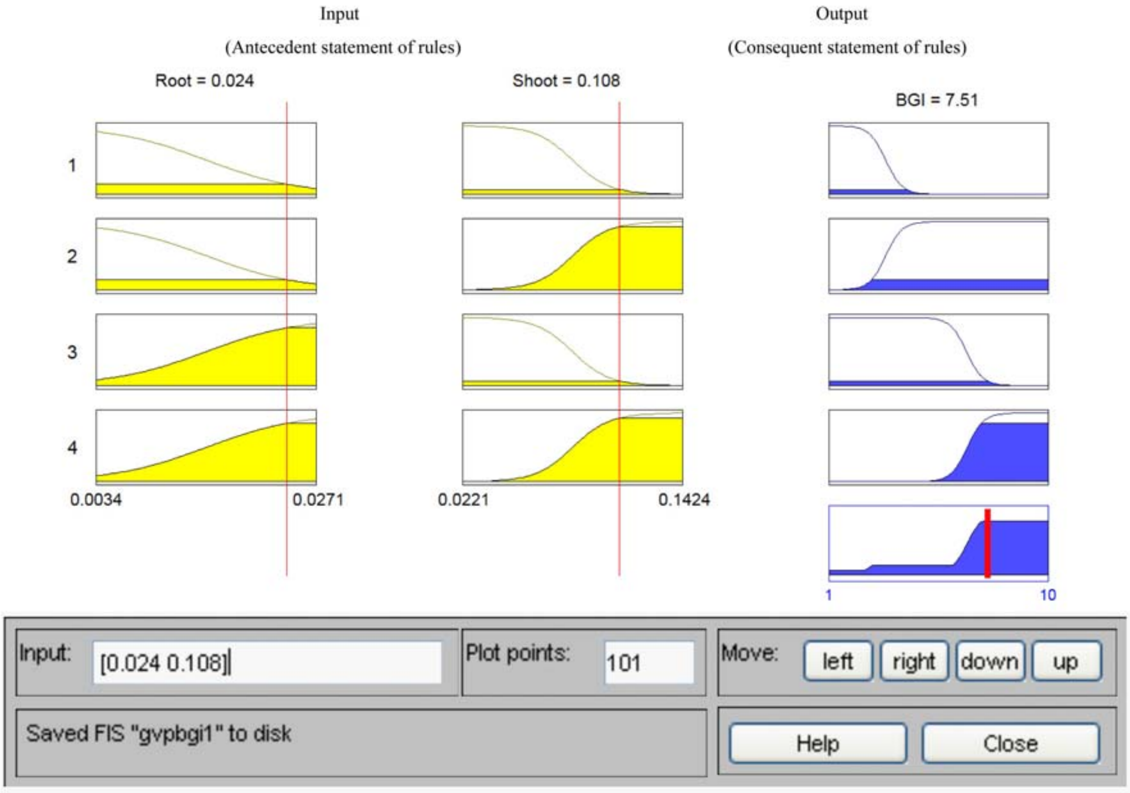

Figure 4 Sample depicting the prediction of BGI for a given input

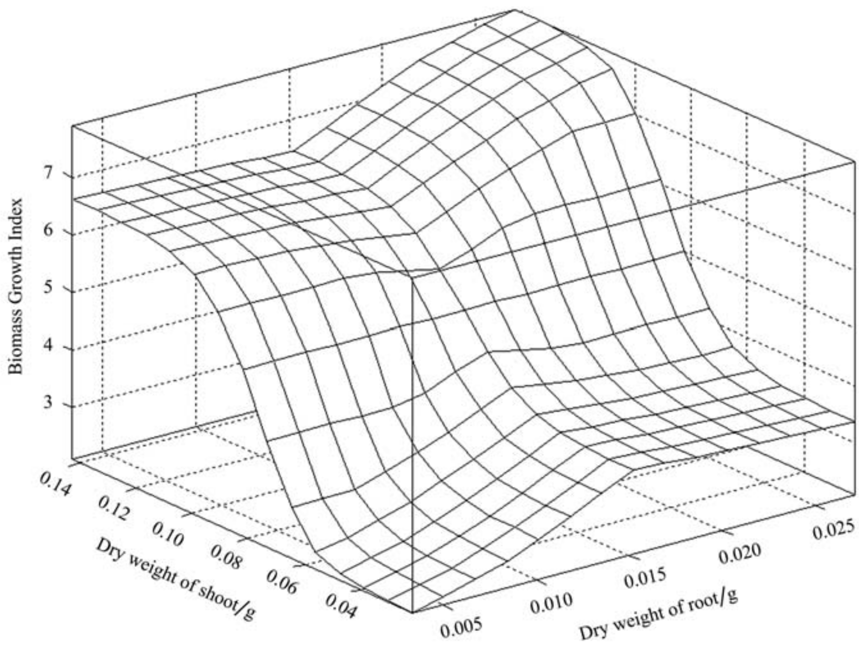

Figure 5 Input-output surface after defuzzification of sigmoidal membership function for input and output

3.4 MF for the fuzzy logic model

In the present study, MF was constructed subjectively. The conventional approach of the subjective construction of MF is to first pick the shape of the MF (given in Section 2.2) and then fine-tune the values of the parameters of that function. The output of the fuzzy logic model, BGI, is only a rational number and there is no actual values of BGI to fine tune the parameters of the MF of the model. Therefore, treatments were assigned the rank based on the root:shoot ratio as explained in Section 3.5. The mean values of the dry weight of root biomass and the dry weight of shoot biomass were fed to the fuzzy logic model taking one MF at a time and BGI of the all treatments were determined. The treatment with the highest BGI was assigned rank 1. All the treatments were assigned the rank according to the descending order of their BGI. The parameters of the MF were fine-tuned to obtain the rank of each treatment at par with that of the root:shoot ratio. During tuning, same MF was used for both input and output variables. Fuzzy sets were equally spaced throughout the input-output space and MF of equal slope was used for the fuzzy sets of each variable. Thus, treatments were assigned the rank using each MF in the fuzzy logic model. The rank assigned by the fuzzy logic model for all the treatments was compared with the rank assigned by using the root:shoot ratio. The mean absolute deviation in assigning the rank to treatments was calculated. The fuzzy logic model with MF that resulted in the lowest mean absolute deviation in the rank was selected as the most suitable MF for modeling the biomass growth of the seedling.

3.5 Assigning rank to treatments based on root: shoot ratio

The mean value of the root:shoot ratio of the seedlings belonging to each treatment was calculated. In general, the root:shoot ratio is used to study the effect of the treatment on the growth of the seedlings in comparison with the control group. Higher value of the root: shoot ratio for the seedlings belonging to a treatment in comparison to that belonging to the control group is considered to be a positive effect. However, it is better if a high root:shoot ratio is the result of the increase in weight of the root biomass rather than the decrease in the weight of the shoot biomass. Hence, an increase in the root:shoot ratio of a seedling subjected to one treatment in comparison with another seedling subjected to a different treatment always needs to be checked for whether the increase is due to the increase in the dry weight of the root biomass or the decrease in the dry weight of the shoot biomass. The procedure involved in assigning the rank to treatment is as follows:

1) One of the treatments was considered as the ‘control’ (C). The root:shoot ratio of other treatments were compared with ‘control’. The treatments, whose root: shoot ratio is higher than that of the ‘control’ were listed along with the dry weight of root and shoot biomasses. This list was called group A. Similarly, the remaining treatments whose root:shoot ratio is lower than that of the ‘control’ were listed along with the dry weight of root and shoot biomasses. This list was called group B.

2) The treatments in group A were considered first for the analysis. The absolute percent deviation of the dry weight of root and shoot biomasses of each treatment in A from that of the ‘control’ were determined as follows:

$$\lambda_i = \frac{(s_i - c)}{c} \times 100$$

Where, λ_i = absolute percent deviation of the dry weight of root or shoot biomass of i^{th} treatment from that of ‘control’; s_i = dry weigh of root or shoot biomass of i^{th} treatment; c = dry weight of root or shoot biomass of ‘control’.

3) The number of treatments, whose percent deviation of the dry weight of root biomass is positive and its absolute value is higher than the absolute value of the percent deviation of its dry weight of shoot biomass, was determined. Let it be j. It indicates the number of treatments whose root:shoot ratio is higher than the ‘control’ due to the higher influence of the increased root biomass than the decreased shoot biomass.

4) The treatments in group B were considered next for the analysis. The absolute percent deviation of the dry weight of root and shoot biomasses of the treatments in B from that of the ‘control’ were determined as above.

5) The number of treatments, whose percent deviation of the dry weight of shoot biomass is positive and its absolute value is higher than the absolute value of the percent deviation of its root biomass, was determined. Let it be k. It indicates the number of treatments whose root:shoot ratio is lower than the ‘control’ due to higher influence of the increased shoot biomass than the decreased root biomass.

6) The rank of the treatment considered as ‘control’ is given by $j + k + 1$.

7) Steps *1* to *6* were repeated for each treatment. The rank of all treatments was determined.

3.6 Identification of the best treatment combination for the production of seedlings

The best combination of the potting mix and the pot volume for the production of paper pot seedlings is the one that produces seedlings with high BGI at the end of the seedling stage, low in cost, and light in weight (Kumar and Raheman, 2012). This is a multi-objective optimization problem. The objectives (BGI, cost, and weight) conflict with each other in the sense that the potting mix which produces seedlings with high BGI may be from the large pot size (heavy weight) and the mix may be costly due to the higher content of vermicompost and volume. On the other hand, the use of small size pots reduces the weight of pots and the cost of its preparation, but may produce seedlings with low BGI. Hence, it is impossible to obtain a single set of values of the design variables (potting mix and pot size) that corresponds to the best of all the objectives.

In this situation, an optimal solution (potting mix and pot size) represents a certain level of trade-offs among all of the objectives, and a set of trade-off solutions exists for a multi-objective optimization problem. The set containing all the trade-off solutions is called the Pareto front (Coello, 1999), and the solutions on the Pareto front are also called non-dominated solutions. Therefore, solving a multi-objective optimization problem refers to obtaining a subset of the solutions on the Pareto front instead of getting each objective's optimum.

3.6.1 Pareto dominance

In a minimization problem of m objectives, solution x dominating solution y is defined by

$$x < y \,\middle|\, \forall_i : f_i(x) \le f_i(y) \text{ and } \exists_j : f_j(x) < f_j(y)$$

where, $f_i(x)$ and $f_i(y)$ are the values of the i-th objective corresponding to x and y respectively. The meaning of the above definition is that all the objectives corresponding to solution x are smaller than or equal to those corresponding to y, and there exists at least one objective whose value for x is smaller than that for y. If x does not dominate y and vice versa, the two are said to be non-dominated. A set of non-dominated solutions is called a non-dominated front. For solutions of a given population, there may be multiple non-dominated fronts (Deb et al., 2002). However, solutions in the first front have higher preference in the selection process than those in other fronts, because the latter is dominated by the former.

3.6.2 Procedure for non-dominated sorting

In the present study, BGI has to be maximized, whereas the cost and weight have to be minimized. In order to convert it into a problem of minimization of all the objectives, the reciprocal of BGI was taken. The pseudocode of non-dominated sorting is illustrated in Figure 6. In Figure 6, P is the population containing 20 sets of combination of potting mix and pot size along with BGI of seedlings, cost, and weight values. The individual solution containing one set of combination of potting mix and pot size along with BGI of seedlings, cost, and weight values is represented by p as well as q. S_p is the set that contains all the individual solutions that is being dominated by p. N_p is the number of individual solutions that dominates p. F_1 refers to the non-dominated front. Steps involved in non-dominated sorting are given below:

1) One individual solution (p) from the population (P) of solutions was taken up.

2) This solution was compared with other solutions (q) in P. A set (S_p) of solutions that p dominated was generated as per the definition of Pareto dominance. The number of solutions (N_p) that dominated p was determined.

3) Steps 1 and 2 were repeated for each individual solution in the population.

4) The non-dominated front (F_1) was developed with individual solutions that has N_p = 0. The front F_1 was stored.

Any solution in the front F_1 containing the combination of potting mix and pot size could be selected as the best solution. However, the solution that dominates the maximum number of solutions is generally taken as the best among the solutions in the front.

```
Non-dominated sorting (P)
F1 = Φ
For each p ∈ P
        Sp = Φ
        Np = 0
        For each q ∈ P
                If (p < q) Then Sp = Sp ∪ {q}
                Else if (q < p) Then Np = Np + 1
        If Np = 0 Then F1 = F1 ∪ {p}
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Figure 6 Pseudocode for non-dominated sorting

4 Results and discussion

4.1 Fuzzy logic model

The rank of each treatment based on the root:shoot ratio and the fuzzy logic model with various MFs is shown in Table 2 for the tomato seedlings. Among the treatments, T7 produced the tomato seedlings of the highest biomass growth. The fuzzy logic model with triangular, Gauss, bell, and sigmoidal MFs identified T7 as the best treatment for the growth of the tomato seedlings. But, the fuzzy logic model with trapezoidal and S shaped MF assigned rank 1 to treatment, T13. Among various MFs, triangular, Gauss, and bell MFs assigned correct rank to 11 treatments. Models with trapezoidal and sigmoidal MF assigned correct rank to nine and six treatments respectively. However, the model with sigmoidal MF assigned rank to all the treatments very close to the rank assigned using the root:shoot ratio with the maximum absolute deviation of 3 for only one treatment. The mean absolute deviation in rank to the treatments (0.95) and the standard deviation (0.83) was also found to be the lowest for the model with sigmoidal MF. Therefore, the fuzzy logic model with sigmoidal MF can be used for categorizing the seedlings subjected to various treatments. The treatment with the highest BGI can be directly selected as the best treatment followed by treatments with subsequent lower values as the next best for the growth of seedlings.

Table 2 Rank assigned by root:shoot ratio and fuzzy logic model with various MFs for tomato seedlings

Treatment designation	Root:shoot ratio	Triangular MF		Trapezoidal MF		Gauss MF		Bell MF		Sigmoidal MF		S shaped MF	
	Rank	BGI	Rank	BGI	Rank	BGI	Rank	BGI	Rank	BGI	Rank	BGI	Rank
T1	16	4.486	16	4.004	16	4.511	16	4.147	16	5.854	14	5.496	14
T2	6	5.874	8	7.566	7	5.804	8	6.619	7	7.002	5	6.966	3
T3	8	6.016	6	7.904	5	5.916	5	6.72	5	6.919	7	6.511	9
T4	10	5.901	7	7.436	8	5.826	7	6.554	8	6.682	11	6.182	12
T5	4	6.018	5	8.112	4	5.915	6	6.788	3	7.127	3	7.189	2
T6	3	5.797	9	7.353	9	5.723	9	6.471	9	7.039	4	6.912	4
T7	1	6.745	1	8.498	2	6.38	1	7.266	1	7.382	1	6.904	5
T8	12	6.226	3	7.592	6	6.041	3	6.639	6	5.819	15	5.454	15
T9	5	6.071	4	8.134	3	5.957	4	6.786	4	6.995	6	6.621	8
T10	12	5.573	12	6.687	12	5.548	12	6.17	12	6.729	10	6.476	10
T11	14	5.416	14	6.162	14	5.406	14	5.881	14	6.454	13	6.144	13
T12	15	5.28	15	5.523	15	5.276	15	5.526	15	4.696	16	4.831	16
T13	2	6.367	2	8.858	1	6.161	2	7.099	2	7.325	2	7.345	1
T14	11	5.696	11	6.935	11	5.658	11	6.37	11	6.798	9	6.653	7
T15	13	5.546	13	6.492	13	5.526	13	6.124	13	6.61	12	6.378	11
T16	8	5.71	10	7.238	10	5.666	10	6.389	10	6.916	8	6.744	6
T17	18	4.05	17	2.055	17	4.141	17	3.291	17	2.871	17	2.867	18
T18	19	3.611	19	1.085	19	3.826	19	2.878	19	2.65	19	2.526	19
T19	18	3.625	18	1.587	18	3.835	18	2.955	18	2.796	18	3.214	17
T20	20	1.472	20	1.085	19	2.962	20	2.073	20	2.157	20	1.44	20
Max. absolute deviation in rank			9		6		9		6		3		4
Mean absolute deviation in rank			1.35		1.3		1.45		1.15		0.95		1.75
Standard deviation			2.35		1.84		2.37		1.87		0.83		1.21

Parameters of the sigmoidal MF for the fuzzy sets of the dry weight of the root biomass and the shoot biomass were a = ±200 and a = ±100 respectively, with c equal to mid-value of the range of each variable. The negative value of a was for the fuzzy set 'low', and the positive value was for the fuzzy set 'high'. The parameters of sigmoidal MF for fuzzy set 'poor', 'moderate', 'good', and 'very good' were, a = –3; c = 3.33, a = 3; c = 3.33, a = –3; c = 6.67, and a = 3; c = 6.67 respectively.

4.2 Validation of the developed model

BGI and rank of each treatment assigned to eggplant and chili peppers seedlings based on the fuzzy logic model and root:shoot ratio are shown in Table 3. The rank assigned to all the treatments based on the developed model was very close to that assigned based on root:shoot ratio (standard deviation 0.76 and 1.15 for eggplant and chili peppers, respectively). The fuzzy logic model assigned correct rank to 11 treatments of eggplant seedlings with maximum absolute deviation of 3 for one treatment. The model assigned correct rank to eight treatments of chili peppers seedlings with maximum absolute deviation of 4 for one treatment. The mean absolute deviation in rank to the treatments for the seedlings of eggplant was found to be 0.55 whereas for chili peppers, it was found to be 1.05. This indicates that the developed model has the good generalization ability and it can be used for categorizing seedlings of any vegetables and horticultural crops.

Table 3 Comparison of rank assigned by the developed fuzzy logic model for eggplant and chili peppers seedlings

Treatment designation	Eggplant			Chili peppers		
	Root: shoot ratio	Fuzzy logic model		Root: shoot ratio	Fuzzy logic model	
	Rank	BGI	Rank	Rank	BGI	Rank
T1	20	2.415	19	14	3.827	15
T2	16	3.566	16	15	3.885	14
T3	2	7.259	2	18	3.589	17
T4	9	5.369	8	12	4.37	12
T5	5	6.878	5	3	5.845	5
T6	14	3.855	14	9	4.967	10
T7	7	6.043	6	6	5.633	6
T8	4	6.999	4	7	5.286	9
T9	6	4.798	9	8	4.858	11
T10	10	4.552	10	5	6.031	3
T11	17	2.961	17	1	6.647	1
T12	8	5.823	7	11	5.447	7
T13	13	4.243	13	19	3.297	19
T14	4	7.044	3	10	5.397	8
T15	12	4.493	11	3	6.408	2
T16	1	7.424	1	4	5.846	4
T17	19	2.227	20	20	2.838	20
T18	18	2.676	18	16	3.655	16
T19	11	4.304	12	14	4.206	13
T20	15	3.601	15	18	3.516	18
Max. absolute deviation in rank			3			4
Mean absolute deviation in rank			0.55			1.05
Standard deviation			0.76			1.15

Determination of the dry weight of seedling involves the destructive method of evaluation of seedling growth and quality. Any other morphological parameters that can be determined by non-destructive methods can also be used instead of the dry weight of root and shoot biomasses as input to the model. The development of the fuzzy logic model for the growth of seedling is relatively easier than the statistical and artificial neural network model. The development of the fuzzy logic model do not require enormous amount of noise-free input-output (quantitative) data as required by the statistical and neural network models. Besides, the fuzzy logic model can cope with the imprecision involved in the measurement of input parameters of the model.

4.3 Best combination of potting mix and pot volume for the production of paper pot seedlings

The non-dominated set of combination of potting mix and pot volume along with BGI of seedlings, the cost of preparation of 1000 pots and the weight of the pot for tomato, eggplant, and chili peppers are presented in Table 4. T13 and T5 dominated 14 other treatments and found to be best for the production of paper pot seedlings of tomato. However, T5 was selected as best treatment as it was found to be cheaper and slightly heavier than T13.

Table 4 Non-dominated set of potting mix and pot size along with BGI, cost of preparation of 1000 pots and weight of pot

Treatment designation	BGI	Cost, Indian Rupees per 1000 pots	Weight /g	Number of solutions dominated
Tomato				
T13	7.319	426.04	55.807	14
T5	7.120	404.35	64.637	14
T9	6.988	410.46	63.251	12
T7	7.377	498.72	102.445	4
T1	5.854	400.01	72.903	4
T17	2.865	426.55	52.110	3
Eggplant				
T5	6.878	404.35	64.637	11
T14	7.044	474.87	70.438	8
T9	4.798	410.46	63.251	8
T13	4.243	426.04	55.807	5
T3	7.259	491.84	115.545	3
T17	2.227	426.55	52.110	0
T16	7.424	597.14	108.124	0
T1	2.415	400.01	72.903	0
Chili peppers				
T5	5.845	404.35	64.637	11
T10	6.031	455.21	79.834	8
T9	4.858	410.46	63.251	6
T15	6.408	533.10	88.449	5
T11	6.647	508.41	100.248	5
T1	3.827	400.01	72.903	2
T17	2.838	426.55	52.110	0
T13	3.297	426.04	55.807	0

The potting mix should be heavy enough to avoid frequent tipping over yet light enough to facilitate handling (Kumar and Raheman, 2012). Further, treatment T5 has the pots that occupy less space (50 cm^3) than that of T13 (80 cm^3). Hence, trays can carry more number of pots during transport and operation. Treatment, T5 dominated 11 other treatments and was found to be best treatment for the production of paper pot seedlings of eggplant and chili peppers (Table 4). Thus, for all three vegetables selected in the present study, soil based potting mix with 25% vermicompost by volume (M2) in 50 cm^3 paper pot (V1) was found to be the best combination of potting mix and pot size for raising vegetable seedlings.

5 Conclusions

A fuzzy logic model and Pareto dominance criterion were used to identify the best combination of potting mix and pot volume for the production of paper pot seedlings of vegetables (suitable for mechanical transplanting). The fuzzy logic model used simple expert system rules based on the root and shoot biomass growth to categorize the seedlings subjected to various treatments, and its categorization ability was found to be reasonably good. Any other morphological parameters can be used in the model with the same sigmoidal MF to categorize the seedlings. The treatment that results in the seedling with the highest BGI could be directly selected as the best treatment for the growth of seedling. The output (BGI) of the model along with the cost of preparation of pots and the weight of pot for various treatments were used as input to the Pareto dominance criterion for the identification of best treatment combination for the large scale production of seedlings. Among the set of non-dominated solutions, paper pots of 50 cm^3 volume filled with mix of 25% vermicompost and 75% sand and soil in equal proportion by volume was selected for the large scale production of the seedlings of tomato, eggplant and chili peppers. The proposed fuzzy logic model is very easy to develop and when it is coupled with Pareto dominance criterion, it can be effectively used in the decision support system for the identification of best combination of treatment for the seedling production.

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