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Fuzzy Cognitive Map-Based Analysis for Optimizing Watermelon Production Management

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Abstract: This study presents an in-depth investigation of watermelon cultivation in Bangladesh, focusing on the assessment of production levels, costs, influential factors, and the application of Fuzzy Cognitive Map (FCM) technology for precision agriculture. Utilizing degree centrality and closeness centrality measures, the FCM model is employed to systematically examine the interplay among various elements involved in watermelon cultivation in Bangladesh and to elucidate the impacts of these factors on production yield. The findings contribute to the advancement of precision agriculture practices and provide valuable insights for optimizing watermelon production management in Bangladesh.

Keywords: Watermelon production; Fuzzy cognitive maps; FCM algorithm; Directed graph; Degree centrality; Closeness centrality

1 Introduction

Watermelon is a highly sought-after fruit, known for its sweet and refreshing taste. In recent years, its cultivation has gained popularity, particularly in coastal regions, due to the substantial profit margins it offers to farmers. As a result, watermelon production has played a significant role in improving the socio-economic conditions of many individuals.

According to the Bangladesh Bureau of Statistics, the total watermelon yield in the 2019-20 fiscal year reached 254,814 metric tons, cultivated on 30,262 acres of land, with an average production of 8,420 kg per acre. In the following fiscal year, 345,955.44 metric tons were produced on 40,860.73 acres of land, yielding 8,466.70 kg per acre. The Department of Agricultural Marketing (DAM) reported that the average production cost per kg of watermelon in the 2020-2021 fiscal year was Tk. 8.68, with a per-acre cost of Tk. 92,869. Considering a selling price of Tk. 26 per kg, an acre of watermelon cultivation generated a substantial profit of Tk. 188,755 for farmers.

Agricultural production is inherently influenced by various factors, including seasonal and climatic variations, soil type, moisture content, and soil composition. The complex, nonlinear relationships among these factors create challenges in accurately predicting crop yields. To address this issue, Kosko (1994) introduced the Fuzzy Cognitive Map (FCM) technique, which overcomes the limitations of traditional statistical models and the subjectivity of human expertise by aggregating expert opinions to determine the strength of relationships among factors influencing yield [1].

FCMs have been demonstrated as an effective modeling method in precision agriculture, with learning methodologies based on algorithms developed for induced fuzzy cognitive maps to adapt cause-and-effect relationships in FCM models [2]. This approach enhances the effectiveness and strength of FCMs by updating the initial knowledge of human experts and integrating their structural knowledge [3]. In light of these advancements, the present study aims to apply FCM technology, coupled with its learning capabilities, to model watermelon production levels under various agro-climatic conditions. This novel application of FCMs in the context of watermelon cultivation has the potential to contribute valuable insights for optimizing production management and precision agriculture practices.

2 Fuzzy Cognitive Maps

2.1 Background and Description

FCMs have their foundation in graph theory, which was introduced by Euler in 1736. Directed graphs (digraphs) were later employed to investigate real-world structures. Signed digraphs were used to represent information sources, with the term "cognitive map" describing the graphed causal links between variables. Kosko first coined the term "fuzzy cognitive map" to characterize a cognitive map model with two distinguishing features: (a) fuzzy causal relationships between nodes, and (b) dynamic feedback, where changes in one node affect other nodes, which can, in turn, influence the initiating node. The FCM structure is analogous to a recurrent artificial neural network, where concepts are represented by neurons and causal relationships by weighted links connecting the neurons. The concepts encompass the system's characteristics, properties, qualities, and senses. The causal relationships between the concepts are demonstrated through their connections, highlighting the cause-and-effect influence of one FCM concept on the others. These weighted connections indicate the direction and strength of the influence that one concept exerts on others. Figure 1 illustrates the graphical representation of a Fuzzy Cognitive Map [4].

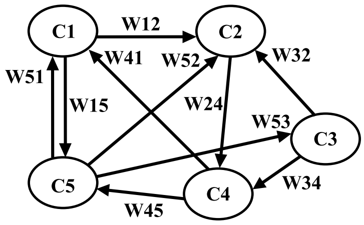

Figure 1. A simple fuzzy cognitive map

The connection strength between two nodes, c_i and c_j, is represented by w_{ij}, which takes a value in the range of -1 to 1. There are three possible types of causal relationships among concepts:

•$w_{ji} > 0$, which indicates a positive causality between concepts C_j and C_i. An increase in the value of C_j leads to an increase in the value of C_i, and a decrease in the value of C_j results in a decrease in the value of C_i.

•$w_{ji} < 0$, which indicates a negative causality between concepts C_j and C_i. An increase in the value of C_j leads to a decrease in the value of C_i, and a decrease in the value of C_j results in an increase in the value of C_i.

$w_{ji} = 0$, which indicates no relationship between C_j and C_i.

2.2 Preliminaries

Definition 2.2.1

A fuzzy cognitive map is associated with directed graphs, where concepts are represented as nodes and the edges represent their causality. If an increase (or decrease) in one concept/node results in an increase (or decrease) in another one, the value is assigned as 1 ; otherwise, the value would be -1 . If no connection exists between concepts, the value would be 0 . Consider an FCM with n nodes $C_1, C_2, C_3, \ldots, C_n$, and the directed graph is drawn with weights $w_{ij} \in \{1, -1, 0\}$. A square matrix defined by $E = (w_{ij})$ is said to be an adjacency matrix of the FCM, where w_{ij} represents the weight of the directed edge C_iC_j.

Definition 2.2.2

For an FCM with n nodes $C_1, C_2, C_3, \ldots, C_n$, a vector $A = \{a_1, a_2, a_3, \ldots, a_n\}$ is called an instantaneous state neutrosophic vector with two states of the nodes at an instant, where the state of the node is defined as:

$$a_i = \begin{cases} 0 \text{ when } a_i \text{ is OFF} \quad \text{(no effect)} \\ 1 \text{ when } a_i \text{ is OFF (with effect)} \end{cases} \tag{1}$$

Definition 2.2.3

Consider an FCM with n nodes $C_1, C_2, C_3, \ldots, C_n$ and the edges of the FCM forming a directed cycle as $\overrightarrow{C_1C_2}, \overrightarrow{C_2C_3}, \ldots, \overrightarrow{C_lC_J}$. When an FCM contains a directed cycle, it is classified as cyclic. In contrast, if an FCM lacks a directed cycle, it is considered acyclic. An FCM that includes a cycle is known as a dynamical system. If C_i is activated, and the causality circulates continuously through the cycle's edges, such as $\overrightarrow{C_1C_2}, \overrightarrow{C_2C_3}, \ldots, \overrightarrow{C_{l-1}C_l}$, the resulting equilibrium state is referred to as the hidden pattern. When the equilibrium state of a dynamical system corresponds to a unique state vector, it is termed a fixed point. For instance, if the FCM reaches stability with C_1 and C_n ON, meaning the state vector remains as $(1, 0, 0, \ldots, 1)$, this state vector is called a fixed point.

Definition 2.2.4

For any FCM, if the state vector follows the pattern $A_1 \to A_2 \to \cdots A_i \to A_1$, the equilibrium is called a limit cycle of the FCM.

Definition 2.2.5

Consider a vector $A = (a_1, a_2, \dots, a_n)$ that passes through a dynamical system B. After thresholding and updating the vector AB, we obtain the resulting vector $C = (b_1, b_2, \dots, b_n)$, denoted as $(a_1, a_2, \dots, a_n) \hookrightarrow (b_1, b_2, \dots, b_n)$. The symbol $\hookrightarrow$ depicts that the resulting vector has been thresholded and updated.

2.3 Algorithm

The Induced Fuzzy Cognitive Map (IFCM) focuses on the FCM algorithm, which generates an optimistic solution from unsupervised data [5]. The following steps must be taken to obtain such an optimistic solution for a problem using unsupervised data:

	Algorithm in induced fuzzy cognitive map
Step 1	Collect the nodes for the given unsupervised data problem.
Step 2	Create the directed graph for the model.
Step 3	Generate a connection matrix E from the FCM. The number of rows in this matrix corresponds to the required number of steps.
Step 4	Set the first component of the state vector $V(k_1, C_1$, to the ON position and the remaining components to the OFF position.
Step 5	Compute $M = C_1 \times E$. Update the state vector and threshold at each stage. The threshold value for the product of the result is denoted by the symbol $\hookrightarrow$. The threshold value is calculated from M by assigning the value 1 when $x_i > 0$ and 0 when $x_i \leq 0$.
Step 6	Calculate the product of the given matrix by taking each element of the vector C_1 individually. Identify the vector y_1 containing the most ones (1).
Step 7	When a threshold value is reached twice and the iteration is stopped, this is referred to as a fixed point.
Step 8	Turn on the vector C_2 while turning off the other components. Continue the computation addressed in steps 4 through 7.
Step 9	Repeat the procedure outlined above for each remaining state vector C_n to reveal the hidden pattern.

2.4 Development of FCM Model for Watermelon Production Management Problem

Three agricultural domain experts helped identify the 15 principles that constitute the FCM model for managing watermelon production. These principles represent different soil types, seasonal and weather factors that experts believe influence watermelon production. The decision concept (DC), in this case, the yield category for watermelons, is one of the concepts and is entirely dependent on the 15 concepts listed in the description provided in the Table 1.

Table 1. Concepts with numbers of fuzzy sets

Concepts	**Description**	**Number of fuzzy sets**
C1: pH	pH level of soil	5
C2: EC	Electric conductivity	4
C3: OM	organic matters	3
C4: N	Amount of Nitrogen	4
C5: phosphorous (P)	Olsen method (pH≥6.6) & Bray and Kurtz method (pH≤6.5)	3
C6: K	Amount of potassium	4
C7: S	Amount of Sulphur	3
C8: Zn	Amount of zinc	3
C9: B	Amount of boron	4
C10: Ca	Amount of calcium	4
C11: Mg	Amount of magnesium	4
C12: Cu	Amount of copper	3
C13: Fe	Amount of iron	4
C14: Mn	Amount of manganese	4
C15: Temp	Atmospheric temperature	5
C16: Production	Watermelon production in a season	3

The directed graph of concepts influencing the watermelon production, see Figure 2.

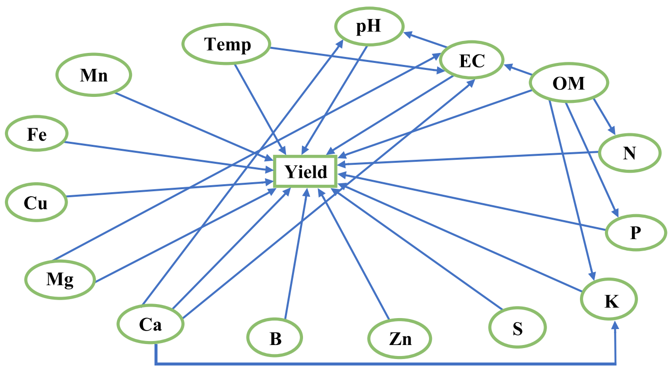

Figure 2. The directed graph

2.5 Qualitative Description of Each Concept and Their Numerical Range

pH		(mS/m)		OM (ppm)		N (ppm)	
Range	Description	Range	Description	Range	Description	Range	Description
< 4	excessively acidic	< 10	not salty	< 0.5	Very Low	< 5	Very low
$4 - 6$	acidic	$10 - 25$	mildly salty	$0.5 - 1.0$	Low	$5 - 20$	Low
$6 - 8$	neutral	$25 - 35$	moderate salty	$1.0 - 2.0$	Medium	$20 - 35$	Medium
$8 - 10$	mildly alkaline	> 35	excessively salty			> 35	Excessive
> 10	excessively alkaline						

K (ppm)		S(μg/g)		P(μg/g)		Zn (ppm)	
Range	Description	Range	Description	Range	Description	Range	Description
$50 - 150$	medium	< 9	Low	< 6.0	Very Low	$0 - 3$	Very low
$150 - 250$	adequate	$9 - 18$	Medium	$6 - 12$	Low	$3 - 5$	Low
$250 - 400$	excessive	> 18	Excessive	$12 - 20$	Medium	$5 - 10$	Medium
> 400	very excessive			> 20	Adequate		

B(μg/g)		Ca (ppm)		Mn (ppm)		Fe (ppm)	
Range	Description	Range	Description	Range	Description	Range	Description
< 0.15	Very low	< 600	Low	< 100	Low	< 10	Low
$0.151 - 0.30$	Low	$600 - 1500$	Adequate	$100 - 250$	Medium	$10 - 15$	Medium
$0.30 - 0.50$	Medium	$1500 - 2000$	Excessive	$250 - 350$	Excessive	$15 - 25$	Excessive
$0.50 - 0.75$	Excessive	> 2000	Very Excessive	> 350	Very Excessive	> 25	Very Excessive
> 0.75	Very excessive						

Cu (ppm)		Mg (ppm)		Temp (Degree Celsius)	
Range	Description	Range	Description	Range	Description
< 6	Low	< 150	Low	< 15	very low
$0.6 - 1$	Medium	$150 - 350$	Adequate	$15 - 20$	low
> 1	Excessive	$350 - 500$	Excessive	$20 - 30$	medium
		> 500	Very excessive	$30 - 40$	excessive
				> 40	very excessive

2.6 Fuzzy Rule Base of the Concepts

Factors	First expert opinion	Second expert opinion	Third expert opinion
C1: pH	When pH is excessively acidic, production is found to be very low.		

Factors	First expert opinion	Second expert opinion	Third expert opinion
	When pH is mildly acidic, it is observed that production remains very low.		
	When pH is neutral, the result is a high production.	If pH is neutral, that brings the case production is medium	
	When pH is mildly alkaline, the outcome is high production.		
	When pH is excessively alkaline, production is seen to be very low.		
C2: electric conductivity (EC)	When EC is not salty, the production is very low.		
	When EC is mildly salty, the production is low.		
	When EC is moderately salty, the production is high.		
	When EC is excessively salty, the production is low.		
C3: organic matters (OM)	When OM is very low, the production is very low.		
	When OM is low, the production is very low.		
	When OM is medium, the production is medium.		
C4: nitrogen (N)	When N is very low, the production is low.		
	When N is low, the production is low.		
	When N is medium, the production is high.		
	When N is excessive, the production is low.		
C5: phosphorous (P)	When P is low, the production is low.		
	When P is medium, the production is low.		
	When P is adequate, the production is high.		If P is adequate, that brings the case production is medium
C6: potassium (K)	When K is medium, the production is low.		
	When K is adequate, the production is high.	If K is adequate, that brings the case production is medium	
	When K is excessive, the production is low.		
	When K is very excessive, the production is very low.		
C7: sulfur (S)	When S is low, the production is low.		
	When S is medium, the production is moderate.		
	When S is excessive, the production is moderate.		

Factors	First expert opinion	Second expert opinion	Third expert opinion
C8: zinc (Zn)	When Zn is very low, the production is very low.		
	When Zn is low, the production is medium.		
	When Zn is medium, the production is medium.		
C9: boron (B)	When B is very low, the production is very low.		
	When B is low, the production is low.		
	When B is medium, the production is moderate.		
	When B is excessive, the production is low.		
C10: calcium (Ca)	When Ca is low, the production is low.		
	When Ca is adequate, the production is high.		
	When Ca is excessive, the production is medium.		
	When Ca is very excessive, the production is low.		
C11: magnesium (Mg)	When Mg is low, the production is low.		
	When Mg is adequate, the production is medium.		If Mg is adequate, that brings the case production is high
	When Mg is excessive, the production is high.		
	When Mg is very excessive, the production is very low.		
C12: copper (Cu)	When Cu is low, the production is low.		
	When Cu is medium, the production is medium.		
	When Cu is excessive, the production is low.		
C13: iron (Fe)	When Fe is low, the production is low.		
	When Fe is medium, the production is medium.		
	When Fe is excessive, the production is medium.		
	When Fe is very excessive, the production is low.		
C14: manganese (Mn)	When Mn is low, the production is low.		
	When Mn is medium, the production is medium.	If Mn is medium, that brings the case production is high	
	When Mn is excessive, the production is high.		
	When Mn is very excessive, the production is low.		

Factors	First expert opinion	Second expert opinion	Third expert opinion
C15: Atmospheric temperature (Temp)	When the temperature is very low, the production is very low. When the temperature is low, the production is low. When the temperature is medium, the production is medium. When the temperature is excessive, the production is high. When the temperature is very excessive, the production is low.		If temperature is medium, that brings the case production is high

2.7 Implementation of FCM Model to the Study

The watermelon production factors (pH, EC, OM, N, P, K, S, Zn, B, Ca, Mg, Cu, Fe, Mn, Temp) are used as the row and column headers, respectively, to create the connection or adjacency matrix M. Values are assigned as 1 if there is a relationship between nodes and 0 if there isn't. To investigate the problem, we will use three different scenarios. In case 1, the active concepts are pH, EC, OM, N, and Production (Tables 2-7). In case 2, the activated concepts are K, S, Zn, B, Ca, and Production (Tables 8-14). Finally, in case 3, the activated concepts are Mg, Cu, Fe, Mn, Temp, and Production (Tables 15-20).

Table 2. The connection matrix for Case-1

Case 1	pH	EC	OM	N	Production
pH	0	1	0	0	1
EC	1	0	1	0	1
OM	0	1	0	1	1
N	0	0	1	0	1
Production	1	1	1	1	0

Table 3. FCM processing when pH=1

C_1M	$=$	$(0,1,0,0,1)$			$=$	C_2	
C_2M	$=$	$(2,1,2,1,1)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$(2,3,3,2,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 4. FCM processing when EC=1

C_1M	$=$	$(1,0,1,0,1)$			$=$	C_2	
C_2M	$=$	$(1,3,1,2,2)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$(2,3,3,2,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 5. FCM processing when OM=1

C_1M	$=$	$(0,1,0,1,1)$			$=$	C_2	
C_2M	$=$	$(2,1,3,1,2)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$((2,3,3,2,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 6. FCM processing when N=1

C_1M	$=$	$(0,0,1,0,1)$			$=$	C_2	
C_2M	$=$	$(1,2,1,2,1)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$((2,3,3,2,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Assume that the concept pH is active and all other nodes are in an inactive mode for individuals in our directed graph of watermelon production. Thus, pH equals 1. This is represented by the vector C_1 = (1,0,0,0,0). The processing according to the algorithm in the Induced Fuzzy Cognitive Map is given in Table 2.

Table 7. FCM processing when Production=1

C_1M	$=$	$(1,1,1,1,0)$			$=$	C_2	
C_2M	$=$	$(1,2,2,1,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$((2,3,3,2,4)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 8. The connection matrix for Case-2

Case 2	**K**	**S**	**Zn**	**B**	**Ca**	**Production**
K	0	0	0	0	1	1
S	0	0	0	0	0	1
Zn	0	0	0	0	0	1
B	0	0	0	0	0	1
Ca	1	0	0	0	0	1
Production 1		1	1	1	1	0

Table 9. FCM processing when K=1

C_1M	$=$	$(0,0,0,0,1,1)$			$=$	C_2	
C_2M	$=$	$(2,1,1,1,1,1)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$(2,1,1,1,2,5)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 10. FCM processing when S=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(1,0,0,0,1,5)$	$\hookrightarrow$	$(1,0,0,0,1,1)$	$=$	C_4	
C_4M	$=$	$(2,1,1,1,2,2)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_5	
C_5M	$=$	$(2,1,1,1,2,5)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_6	$\Leftrightarrow C_5$

Table 11. FCM processing when Zn=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(1,0,0,0,1,5)$	$\hookrightarrow$	$(1,0,0,0,1,1)$	$=$	C_4	
C_4M	$=$	$(2,1,1,1,2,2)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_5	
C_5M	$=$	$(2,1,1,1,2,5)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_6	$\Leftrightarrow C_5$

Table 12. FCM processing when B=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(1,0,0,0,1,5)$	$\hookrightarrow$	$(1,0,0,0,1,1)$	$=$	C_4	
C_4M	$=$	$(2,1,1,1,2,2)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_5	
C_5M	$=$	$(2,1,1,1,2,5)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_6	$\Leftrightarrow C_5$

Table 13. FCM processing when Ca=1

C_1M	$=$	$(1,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,2,1)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_3	
C_3M	$=$	$(2,1,1,1,2,5)$	$\hookrightarrow$	$(1,1,1,1,1)$	$=$	C_4	$\Leftrightarrow C_3$

Table 14. FCM processing when Production=1

C_1M	$=$	$(1,1,1,1,1,0)$			$=$	C_2	
C_2M	$=$	$(1,0,0,0,1,5)$	$\hookrightarrow$	$(1,0,0,0,1,1)$	$=$	C_3	
C_3M	$=$	$(2,1,1,1,2,2)$	$\hookrightarrow$	$(1,1,1,1,1,1)$	$=$	C_4	
C_4M		$(2,1,1,1,2,5)$		$(1,1,1,1,1,1)$		C_5	$\Leftrightarrow C_4$

Table 15. The connection matrix for Case-3

Case 3	Mg	Cu	Fe	Mn	Temp.	Production
Mg	0	0	0	0	0	1
Cu	0	0	0	0	0	1
Fe	0	0	0	0	0	1
Mn	0	0	0	0	0	1
Temp	0	0	0	0	0	1
Production	1	1	1	1	1	0

Table 16. FCM processing when Mg=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_4	$\Leftrightarrow C_2$

Table 17. FCM processing when Cu=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_4	$\Leftrightarrow C_2$

Table 18. FCM processing when Fe=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_4	$\Leftrightarrow C_2$

Table 19. FCM processing when Mn=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_2M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_4	$\Leftrightarrow C_2$

Table 20. FCM processing when Temp=1

C_1M	$=$	$(0,0,0,0,0,1)$			$=$	C_2	
C_2M	$=$	$(1,1,1,1,1,0)$			$=$	C_3	
C_3M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_4	$\Leftrightarrow C_2$

Table 21. FCM processing when Production=1

C_1M	$=$	$(1,1,1,1,1,0)$			$=$	C_2	
C_2M	$=$	$(0,0,0,0,0,5)$	$\hookrightarrow$	$(0,0,0,0,0,1)$	$=$	C_3	$\Leftrightarrow C_1$

3 Centrality Measures

Various measures can be employed for evaluating the FCM; however, in this study, the focus is on centrality measures [6–8]. Degree centrality and closeness centrality are utilized to present the findings of the analyses in this section. In a given weighted and directed graph, the degree centrality of each node or concept is determined by summing the absolute weights of its outgoing and incoming edges. This metric indicates the extent to which a concept node in an FCM influences other concept nodes within the network. Closeness centrality is defined as the inverse of the sum of the lengths of the shortest paths connecting a node to all other nodes. This measure demonstrates the rate at which a concept section node affects other nodes in the FCM [9–15].

3.1 Degree Centrality

Degree centrality of a node is determined by the number of edges connected to it. To obtain the standardized score, each value is divided by n-1 (where, n represents the number of nodes). This measure illustrates the extent to which a concept node in an FCM influences other concept nodes within the system (Tables 22-23).

$pH = 3/15 = 0.2$	$EC = 6/15 = 0.4$	$OM = 5/15 = 0.33$
$N = 1/15 = 0.07$	$P = 2/15 = 0.13$	$K = 3/15 = 0.2$
$S = 1/15 = 0.07$	$Zn = 1/15 = 0.07$	$B = 1/15 = 0.07$
$Ca = 4/15 = 0.27$	$Mg = 2/15 = 0.13$	$Cu = 1/15 = 0.07$
$Fe = 1/15 = 0.07$	$Mn = 1/15 = 0.07$	$Temp = 2/15 = 0.13$

Table 22. Closeness centrality measure-part 1

	Nodes															All-inclusive		Intra-component	
	pH	EC	OM	N	P	K	S	Zn	B	Ca	Mg	Cu	Fe	Mn	Temp.	F	C	F	C
pH	0	1	2	3	3	3	inf	inf	inf	1	2	inf	inf	inf	2	inf	0	17	0.06
EC	1	0	1	2	2	2	inf	inf	inf	1	1	inf	inf	inf	1	inf	0	11	0.09
OM	2	1	0	1	1	1	inf	inf	inf	2	2	inf	inf	inf	2	inf	0	12	0.08
N	3	2	1	0	2	2	inf	inf	inf	3	3	inf	inf	inf	3	inf	0	19	0.05
P	3	2	1	2	0	2	inf	inf	inf	3	3	inf	inf	inf	3	inf	0	19	0.05
K	3	2	1	2	2	0	inf	inf	inf	1	3	inf	inf	inf	3	inf	0	17	0.06
S	inf	inf	inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	inf	inf	0	0	inf
Zn	inf	inf	inf	inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	inf	0	0	inf
B	inf	inf	inf	inf	inf	inf	inf	inf	0	inf	inf	inf	inf	inf	inf	inf	0	0	inf
Ca	1	1	2	3	3	1	inf	inf	inf	0	2	inf	inf	inf	2	inf	0	15	0.07
Mg	2	1	2	3	3	3	inf	inf	inf	2	0	inf	inf	inf	2	inf	0	18	0.55
Cu	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	0	inf	inf	inf	inf	0	0	inf
Fe	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	0	inf	inf	inf	0	0	inf
Mn	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	inf	0	inf	inf	0	0	inf
Te	2	1	2	3	3	3	inf	inf	inf	2	2	inf	inf	Inf	0	inf	0	18	0.55

Table 23. Closeness centrality measure-part 2

	Nodes															Closeness	
	pH	EC	OM	N	P	K	S	Zn	B	Ca	Mg	Cu	Fe	Mn	Temp.	Sum	Nor
pH	-	1	0.5	0.33	0.33	0.33	0	0	0	1	0.5	0	0	0	0.5	4.49	0.45
EC	1	-	1	0.5	0.5	0.5	0	0	0	1	1	0	0	0	1	6.5	0.65
OM	0.5	1	-	1	1	1	0	0	0	0.5	0.5	0	0	0	0.5	6	0.60
N	0.33	0.5	1	-	0.5	0.5	0	0	0	0.33	0.33	0	0	0	0.33	3.82	0.39
P	0.33	0.5	1	0.5	-	0.5	0	0	0	0.33	0.33	0	0	0	0.33	3.82	0.39
K	0.33	0.5	1	0.5	0.5	-	0	0	0	1	0.33	0	0	0	0.33	4.49	0.45
S	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0	0
Zn	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0	0
B	0	0	0	0	0	0	0	0	-	0	0	0	0	0	0	0	0
Ca	1	1	0.5	0.33	0.33	1	0	0	0	-	0.5	0	0	0	0.5	5.16	0.51
Mg	0.5	1	0.5	0.33	0.33	0.33	0	0	0	0.5	-	0	0	0	0.5	3.99	0.40
Cu	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0	0	0
Fe	0	0	0	0	0	0	0	0	0	0	0	0	-		0	0	0
Mn	0	0	0	0	0	0	0	0	0	0	0	0	0	-	0	0	0
Te	0.5	1	0.5	0.33	0.33	0.33	0	0	0	0.5	0.5	0	0	0	-	3.99	0.40

3.2 Closeness Centrality

In cases where two nodes are disconnected, the distance between them is considered infinite, as no direct or indirect path connects them. Consequently, the total distances between any two nodes are infinite if at least one is unreachable by the others. Thus, the closeness measure is only applied to the largest node component (measured intra-component). In the subsequent table, F denotes farness, and C represents closeness.

4 Conclusion

This study has identified the most influential factors affecting watermelon production in Bangladesh, including soil pH, electric conductivity, organic matter, N, P, K, Ca, Mg, and temperature. Moreover, it has been found that humidity and seasonal rainfall play significant roles in ensuring optimal yield. With the assistance of experts in the field, a qualitative description of each concept, their numerical range, a directed graph of concepts influencing watermelon production, and a fuzzy rule base of the concepts have been established.

Future research could extend this work by incorporating nonlinear Hebbian learning algorithms (NHL) and data-driven nonlinear Hebbian learning algorithms (DDNHL) using expert opinions and historical records.

Data Availability

The data supporting our research results are included within the article or supplementary material.

Conflicts of Interest

The authors declare no conflict of interest.

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