LAUTECH Journal of Computing and Informatics (LAUJCI) – ISSN: 2714-4194
Volume 1– No.1, Sept. 2020 – www.laujci.lautech.edu.ng

Development of a Forecasting Model for Farm Produce using Fuzzy Cognitive Map

Alo O. O.
Department of Computer Science & Engineering, Ladoke Akintola University of Technology, PMB 4000, Ogbomoso, Nigeria.
ooalo@lautech.edu.ng

Fenwa D. O.
Department of Computer Science & Engineering, Ladoke Akintola University of Technology, PMB 4000, Ogbomoso, Nigeria.
odfenwa@lautech.edu.ng

Adetunji A. B.
Department of Computer Science & Engineering, Ladoke Akintola University of Technology, Ogbomoso,
abadetunji@lautech.edu.ng

ABSTRACT
A Fuzzy Cognitive Maps (FCMs) is a modeling methodology based on exploiting knowledge and experience. It comprises the main advantages of fuzzy logic and neural networks, representing a graphical model that consists of nodes-concepts which are connected with weighted edges (representing the cause and effect relationships among the concepts). FCMs have proved to be a promising modeling methodology with many successful applications in different areas especially for simulating system design, modeling and control. Improving the crop yield has always been a major challenge for farming community as well for agricultural scientists. Though various computational approaches (qualitative and quantitative analysis) have been followed traditionally in practice, still a persistent decision making method to improve crop yield is not yet predicted.
In this work, FCMs are introduced to model a decision support system for precision agriculture (PA). The FCM model developed consists of nodes which describe soil properties and agricultural crop yield and of the weighted relationships between these nodes. The nodes of the FCM model represent the main factors influencing crop production i.e. essential soil properties such as soil texture, temperature, soil fertility, bulk density, pH, annual rainfall, pest infestation among others.
This work provides a clear understanding to agricultural products yield forecasting. The information obtained at the end of this work will be useful to agricultural scientists, farmers and other stakeholders
Keyword: fuzzy cognitive map, model, factors, farm produce, crop yield

1.0 INTRODUCTION

Agricultural activity is not only one of the basic activities of the human society, but also the premise for the development of human society. Besides, it has close relation with the development and stabilization of nowadays society. It is of great significance to monitor the growth level of crops thereby, resulting into a good product or harvest. Obtaining crop conditioning information at early stages in the crop growing season is also very important, sometimes it is even more important than acquiring the exact production after harvest time.
Early estimates of agricultural production are of great importance for agricultural policy and trade. Yield prediction based on the combination of the factors affecting it, this is important for farm management. There is a great need for good estimates of yield and total biomass production. The importance of this factor is more critical when site specific management is considered. Precision farming generates data which, due to their type and complexity, could not be efficiently analyzed by traditional methods.
Crop management traditionally has been based mainly on the experience of the farmer for his field. But later with farm mechanization, the direct connection of the farmer with the field was lost and management was based on yield and soil mean properties. The scientific and effective forecasting method is conducive to correctly guide agricultural production, realize the balance of supply and demand of agricultural commodities, increase peasants' income, and provide decision-making basis for the government to adjust agricultural economic structure and implement targeted macro-control.
Fuzzy Cognitive Maps (FCMs) are a suitable knowledge based methodology for modeling and simulating dynamic systems. From the structural perspective, an FCM can be understood as a fuzzy digraph that describes the behavior of a physical system in terms of concepts (i.e., states, variables or entities). Such concepts involve a precise meaning for the physical system and are connected by signed and weighted causal relationships. Fuzzy Cognitive Maps (FCM) consist a soft computing technique following an approach that is considered to be rather similar to both human reasoning and to the corresponding human decision-making process. The usefulness of the FCM approach in modeling complex systems is represented by an algorithm used to demonstrate it (Papageorgiou and Salmeron, 2013).

2.0 LITERATURE REVIEW

Precision agriculture (PA) is to manage variability arise in the agriculture process. Its helps to attain profitable and sustainable farming activity. PA is a systems approach towards agriculture process to manage low input, high yield and environmental sustainable conditions. Productivity is affected by variability in following ways: Yield variability, Field variability, Soil variability, Crop variability, Variability in anomalous factors, and Management variability (Peiris, Hansen and Zubair, 2008).
Each farmland or the zone of the farm has different capability of production due to different conditions like soil types, environmental conditions and other geographic conditions like- slop, elevation, etc.; so, spatially each land has different response in terms of product yield. Different yield capacity of different farm can be interpreted as yield variability. Field variability means variation in the field topography like – elevation, slop, proximity with water source, etc. Soil variability is the variation in soil fertility because of difference amount of micronutrients in different field. The type of texture of soil is also a variable factor. Crop variability is variation in plant growth and duration of growth. Other anomalous factors like weed infestation, insect infestation, disease condition, wind damage etc., are also varying during the life cycle of the plant. All above mentioned factors affect the performance of agriculture process. An important aspect of PA is to understand the variability of these factors and its effect on the agriculture. Detection of these factors and corrective steps to minimize their effect on farm production is also an objective of PA. In general Precision Agriculture helps to achieve the optimum production in spite of yield, field, soil and all other variability. Various methods are suggested to mitigate the effects of this variability by one or another means (Balakrishnan and Meena,2010)

Factors Affecting Agricultural Product

Temperature is measured in degrees Celsius using a thermometer. Temperature is influence by altitude and topography. Temperature decreases with increase in altitude, such that every 300meters rise in altitude above seal temperature decrease by 1.7-2.2 degree Celsius. Each crop has a temperature range within which it can grow well and produce high yields, they require a narrow temperature. For crop to grow well and produce high yields, they require a narrow temperature range within the cardinal range referred to as optimum range of temperature. Effect of temperature on agriculture is as follow:

i. Livestock feeding more at lower temperature
ii. Quality of some crop produce affected by temperature
iii. High temperature cause at low moisture
iv. At lower temperature, there is higher incidence of disease
v. Germination and growth rate influenced by temperature

Effect of Altitude on Agriculture

Crops perform differently when grown in each these ecological zones and therefore each crop has its most suitable zone for maximum performance as illustrated below:

i. Low altitude zone 0-1500 meters above sea level
ii. Medium altitude zone 1500-2500 meters above sea level
iii. High altitude zone above 2500 meters above sea level

Effect of Light on Agriculture

Light is the source of energy which plants for photosynthesis. During photosynthesis, plants manufacture food using water and carbon dioxide in the presence of sunlight and chlorophyll. As illustrated below:
Light Intensity: This is the strength in which light hits the surface of the earth.
Light Duration: This is the period of time the plants are exposed to light recorded using a Campbell sunshine recorder
Photo-periodism: This is the response of plants towards light duration.
Long-day plants: These are plants which require more than 12hours of lighting to flower and produce fruits or seeds.

Short-day plant: These are plants which require less than 12 hours lighting to flower and produce.
Day-Neutral plants: These are plants which produce flowers regardless of the duration of lighting they have been exposed to.
Light-wavelength: This refers to the type of quality of light. A wavelength is the distance between two corresponding points of a light wave (Kumar, Rajeev,Vinayan,Nagvekar, Venkitaswamy, Rao, Boraiah, Gawankar, Dhanapal , Patil and Bai,2009).

FCM Model Construction

The construction of FCM is very important since the entire system is based on this model. The basic methodology in FCM construction mainly adopts three approaches: producing weight matrices based on historic data, adapting the cause–effect relationships of the FCM based on experts' intervention, and producing weight matrices by combining experts' knowledge and historic data.
The number and type of concepts used in FCM construction are determined by a group of experts in the corresponding field. The experts' knowledge is used to determine the factors that influence the dynamics of the entire system. The experts are able to identify the causal relationships among the different concepts used in the FCM. In FCM construction process, they identify the concepts and determine the interrelationships among the concepts as positively or negatively correlated. They also determine the strength of association between the related concepts in various linguistic terms such as positively high, positive low, negatively high, and negative low.
The linguistic variables suggested by the experts of each interconnection are aggregated using the sum method, and an overall linguistic weight is produced and then defuzzified using CoG (center-of-gravity) method. Finally, the numeric influence factor Rij from concept ''i'' to concept ''j'' is obtained. By this method, the entire relationship matrix among all the concepts of the constructed FCM is established. The concepts along with the interrelationships among them constitute the FCM model that is constructed solely on the basis of experts' knowledge (Papageorgiou, 2014).

2.4 FCM Learning Using Hebbian Learning Algorithm

The Hebbian learning rule is one of the oldest learning rules that specifies how much the weight of the connection between two units, representing the causal weight between the FCM concepts, should be increased or decreased in proportion to the product of their activation. NHL algorithm was first successfully tested and reported by (Papageorgiou, Stylios and Groumpos, 2004). The concepts in FCM can be triggered synchronously in each iteration step using Eq. (1). At each iteration step, the weights Wij (weight from ith concept to jth concept) are updated using Eq. (3), and these modified weights and concept values are used in the next iteration.

$$A_i^{(k)} = f\left(A_i^{(k-1)} + \sum_{\substack{j \neq i \\ j=1}}^{N} A_j^{(k-1)} \times W_{ji}^{(k-1)}\right) \tag{1}$$

Here, in Eq. (1), $A_i^{(k)}$ is the value of concept i in kth iteration. $W_{ji}^{(k-1)}$ is the weight from jth concept to the ith concept in iteration step (k - 1). f(x) is the sigmoid threshold function and is calculated as given in Eq. (2)

$$F(x) = 1/1 + e^{-\lambda x} \tag{2}$$

where k determines the steepness and is a positive value. In the presented study, the value of k is taken as 1.
The learning rule which used in this model is given in Eq. (3). This equation is used in each iteration step to update the weight matrix

$$W_{ij}^{(k)} = W_{ij}^{(k-1)} + \left(\eta_k \times A_j^{(k-1)}\left(A_i^{(k-1)} - \left(A_j^{(k-1)} \times W_{ji}^{(k-1)}\right)\right)\right) \tag{3}$$

where$W_{ji}^{(k)}$ is the updated weight in kth iteration. gk is the learning parameter value in kth iteration, which is a small positive value. In NHL algorithm, only the nonzero weights in the weight matrix are updated, and all the weights which are zero (indicating no relationship between concepts) will remain zero in each iteration. The termination condition is represented in Eq. (4). Here, Ti is the desired target value of the decision concept, DCi is the actual value of the decision concept at iteration i, and e is the tolerance level in the magnitude of the difference in decision concept in two successive iterations. Normally is assumed as a very small positive value like 0.001.

$$F_1 = \sqrt{\sum_{i=1}^{N} (\mathrm{DC}_i - T)^2}$$
$$F_2 = \left|\mathrm{DC}_i^{(k)} - \mathrm{DC}_i^{(k-1)}\right| < e \quad (4)$$

If the learning process is repeated indefinitely without convergence, then the iteration process needs to be stopped and the model needs to be reconstructed with the help of experts. The maximum number of iterations is generally set to a high value like 500, and if the iterations go beyond this level without convergence, then the model needs to be reconstructed, so that it will be able to converge in the desired region (Zhang, Shen and Miao,2011).

Related Work

A detailed survey and analysis of existing works which support decision making approaches ((Liu, Goering and Tian, 2001)) for crop yield are discussed. Applying soft computational and statistical approaches for crop yield analysis is not much considered under major research challenges. In order to derive an accurate crop yield, predictive mining approach on fuzzy cognitive method could prove elusive. Crop yield attributes to some common basic factors which are related to crop growth parameters and disorders parameters such as high rainfall, irrigation procedures, moderate sunlight intensity, rocky soil type which may not attribute to growth of crops in general. Such change in unexpected frequency may affect severity of crop yield as unexpected by farming community.

Markinos et al (2007) introduced FCMs to model a decision support system for precision agriculture (PA). The FCM model developed consists of nodes with described soil properties and cotton yield and the weighted relationships between these nodes. The nodes of the FCM model represent the main factors influencing cotton crop production i.e. essential soil properties such as texture, potential of Hydrogen. The proposed FCM model addresses the problem of crop development and spatial variability of cotton yield, taking into consideration the spatial distribution of all the important factors affecting yield in designing the FCM model for precision farming, one experienced cotton farmer and two experienced soil scientists played the role of experts and designed the FCM model following the developing methodology described.

3.0 METHODOLOGY

Development of FCM Model for Crop Yield Management Problem

The FCM model for yield management comprise of 20 concepts that are identified with the help of three agricultural domain experts. These concepts represent various soil conditions as well as the seasonal and weather parameters that are believed by the experts to influence the productivity. One of the concepts is called the decision concept (DC) in this case the yield category which is dependent on the combined effect of the values assumed by the other 20 concepts enlisted.

The three domain experts opined to finalize the concepts that influence the coconut yield. The experts described the concepts qualitatively in terms of fuzzy values from the fuzzy set as described in Table 3.1. The experts also described the strength of influence of one concept to the other using the fuzzy IF–THEN rules.

The influences between concepts from each expert are then aggregated using the sum method, and the overall influence (i.e., the causal weight) is calculated, which is then defuzzified using the center-of-gravity method as illustrated, and thus a numeric weight is calculated.

Table 3.1 Concepts Influencing the Crop Yield

Concepts	Description
C1: SF	Soil Fertility
C2: OM	Organic matters present in the soil
C3: BD	Bulk density of the soil
C4: Temp	Atmospheric temperature
C5: Humidity	Humidity
C6: Pest	Percentage infection of pest to the plant
C7:EC	Soil electric conductivity
C8: RF	Annual rainfall amount
C9: SM	Surface soil moisture
C10: Ph	pH level of soil
C11: Yield	Annual yield per plant

Construction of FCM Model for Describing Crop Yield

The FCM model for prediction comprises of 12 concepts. These concepts were determined with the help of two Agronomy Professors, one Professor of Agro Climate Research center, one soil scientist and one agricultural farmer who had more than two decades of experience in cultivation. This process was accomplished through a questionnaire, which was prepared for this process and proposed to be filled out by the expert team. The most important input concepts influencing the output concept DOC (Decision Output Concept) were decided by the expert team. The value of the decision concept, the yield, depends on the combined effect of the values assumed for all the input concepts. The lists of concepts identified are shown in Table 3.2.

The set of linguistic variables that every concept takes is given. The experts were asked to describe the relationships between input concepts with the yield (decision concept) as well as its interconnection with other concepts. The known FCM construction approach is used by applying IF-THEN rules to justify their cause and effect suggestions among concepts. Then the inferred fuzzy weights were aggregated and an overall linguistic weight was produced.

The defuzzification method of Center of Area (CoA) (Papageorgiou et al., 2004) converts the fuzzy quantity into a numerical weight within the interval (-1, 1).

Table 3.2 : Component of Soil Fertility

Concept	Description
C12: Ca	Calcium level in the soil
C13: Mn	Manganese level in the soil
C14: Fe	Iron level in the soil
C15: Zn	Zinc level in the soil
C16: Mg	Magnesium level in the soil
C17: Cu	Copper level in the soil
C18: K	Potassium level in the soil
C19: P	Phosphorus level in the soil
C20: N	Nitrogen level in the soil

Algorithm Developed for Describing Crop Yield Fuzzy Cognitive Map Model.

This algorithm is based on 4 most important factors; soil fertility, soil temperature, pH and rainfall

Algorithm for Soil Fertility

If value is less than 35% then (value less than required condition LOW)
Take measures for making it greater than 35% (add fertilizer/ organic manure or Grow root vegetables).
Else if value is between 35%-50% then (value equals required condition Medium)
Else if value is greater than 50% then (value equals required reading High)

Algorithm for Soil Temperature

If Temperature less than 10^0c and Temperature greater than 26^0c then (temperature value is low). Not appropriate conditions for crop.

Else if Temperature greater than 26^0c and Temperature less than 30^0c then (temperature value is required for maximum yield)
This is the ideal condition, so check this IDEAL TEMPERATURE condition to make sure that the environmental conditions are steady)
Else if Temperature greater than 34^0c then (temperature value is High)
This temperature value is considered very high and will affect yield)

Algorithm for Soil pH

If pH reading less than 6.0 then (pH value is Low) Add lime powder through the irrigation system into the farm.
Circulate water regularly in the farm till the pH reaches to required rating.
Else if pH reading greater than 6 but less than 9 then (pH value is Medium)
Circulate Sulphur from the irrigation system into the farm till the pH reaches to required rating.
Else if pH reading greater than 9 then (pH value is High)
The conditions are appropriate for crop farming.

Algorithm for Rainfall

If Rainfall less than 1000mm then (rainfall value is Low).
Not appropriate conditions for crop.
Else if rainfall greater than 1000mm and rainfall less than 2000mm then (temperature value is required for Medium yield)
This is the ideal condition, so check this IDEAL RAINFALL condition to make sure that the environmental conditions are steady)
Else if rainfall greater than 2000mm then (temperature value is High)
This temperature value is considered very high and will affect yield)

4.0 RESULTS AND DISCUSSIONS

FCM Implementation to Study the Effect of Soil Condition

In studying the effects of climate and weather variables on the yielding of products, the FCM model was tested with different scenarios representing different temperature conditions. This study was performed to answer several ‘‘what–if’’ conditions with respect to the variations in climatic conditions and how they affect the crop yielding. Climate variability consists of the variations in rainfall distributions, humidity, and temperature during the various seasons, early withdrawal, and late onset of moon-sun, etc. This study is very useful to the farmers and other stake holders to analyze the various cause–effect relationships of their interest with respect to different weather variables.

The Table 4.1 shows the FCM concept values for each factors considered while Table 4.2 depicts applied fuzzy sets of rules used to determine crop yield.

Table 4.1: Qualitative description of the FCM concept values.

Electric Conductivity (mS/m)		**Organic Matters (ppm)**	
Range	**Output Range**	**Range**	**Output Range**
< 15	Low	< 1.0	Low
15 – 35	Medium	1.0 – 2.0	Medium
> 35	High	> 2.0	High
Bulk Density (g/cm^3)		**Temperature (0c)**	
Range	**3 Output Range**	**Range**	**Output Range**
0 – 1.3	Low	10 – 26	Low
1.3 – 1.9	Medium	26 – 34	Medium
> 1.9	High	> 34	High
Humidity (%)		**Pest (%)**	
Range	**Output Range**	**Range**	**Output Range**
< 45	Low	< 30	Low
45 – 70	Medium	30 – 50	Medium
> 70	High	> 50	High
Rainfall (mm)		**Soil Fertility (ppm)**	
Range	**Output Range**	**Range**	**Output Range**
< 1000	Low	< 35	Low
1000 – 2000	Medium	35 – 50	Medium
> 2000	High	> 50	High
Soil PH (1-14)		**Soil Moisture (%)**	
Range	**Output Range**	**Range**	**Output Range**
< 6	Low	< 44	Low
6 – 9	Medium	46 – 65	Medium
> 9	High	> 65	High

Table 4.2: Applied Rules in the Model

If soil fertility is	**If rainfall is**	**If temperature is**	**Then the yield is**
Low	Low	Low	Low
Low	Low	Medium	Low
Low	Low	High	Low
Low	Medium	Low	Low
Low	Medium	Medium	Low
Low	Medium	High	Low
Low	High	Low	Low
Low	High	Medium	Low
Low	High	High	High
Medium	Low	Low	Low
Medium	Low	Medium	Low
Medium	Low	High	Medium
Medium	Medium	Low	Medium
Medium	Medium	Medium	Medium
Medium	Medium	High	Medium
Medium	High	Low	Medium
Medium	High	Medium	Medium
Medium	High	High	High
High	Low	Low	Low
High	Low	Medium	Medium

High	Low	High	High
High	Medium	Low	Medium
High	Medium	Medium	Medium
High	Medium	High	High
High	High	Low	High
High	High	Medium	High
High	High	High	High

Crop Yield Prediction

The interface in figure 4.1 shows the crop yield prediction tool (software), this software tool accepts predictions of soil conditions and hereby forecast the product likely output. For each input, indicated by different colours which show that a condition is likely “low (red)”, “medium (orange)” or “High (green)”. These inputs are logically compared to determine the overall forecast output with two columns of “verdict” and “analysis”. The “verdict” will compare all given input and produce the overall output while the “analysis” will summarize some of the main factors that warrant the overall output.
This prediction tool uses the ten parameters considered in this study to be the factors that affect the yield of crops as its input values. The application is designed to display 3 different colour indicators, Green for HIGH input value, Orange for MEDIUM input value and Red for LOW input value. The overall result is determined by combination of the fuzzy cognitive map conditions (If HIGH …THEN, ELSE).

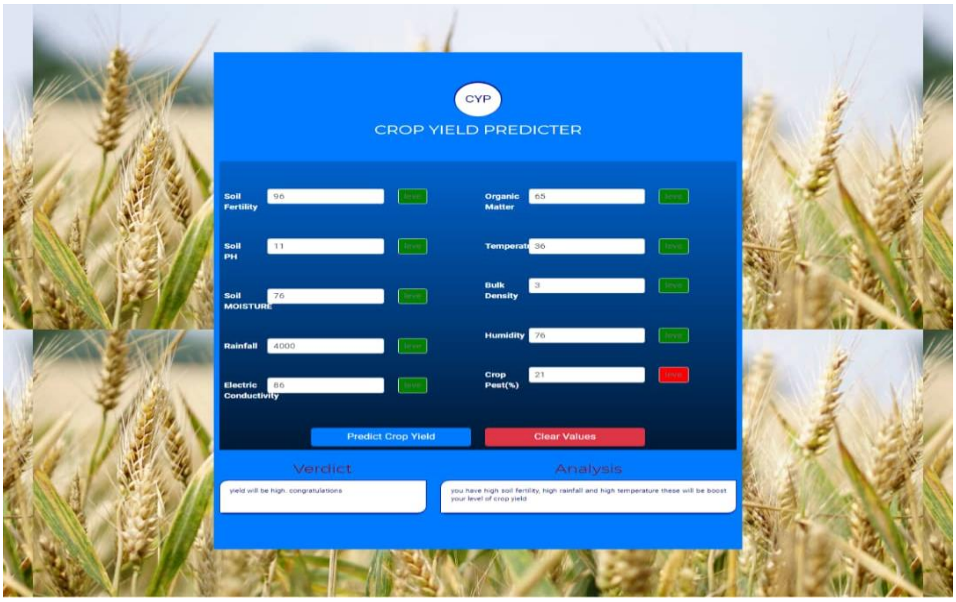

Figure 4.1: User interface of the crop yield prediction software

Simulation of the Developed Fuzzy Cognitive Map Model

The model of factors affecting the yield of crop using fuzzy cognitive map is applied to predict the possibility of crop yield as shown in figure 4.2**.** The figure 4.2 further illustrates the (Fuzzy Cognitive Map diagram/graph) relationship between these variables, shows how one variable contributes to the overall forecast of crop yield in the application. Its depicts each factors that can affect crop yield, a fuzzy value is assigned to each factor between -1 to 1, i.e -1 = low, (red) 0 = medium (orange) and 1 = high. The value of each factor is taken in the model to determine the overall output. The output values for soil fertility, rainfall, and soil temperature are be taken as most important factors of all the ten factors considered. The logical condition/fuzzy cognitive map condition is that

IF at least 1 of the 3input values is HIGH, 1 MEDIUM and 1LOW, THEN
The overall output is high; meaning the crop yield will be MEDIUM.

ELSE
IF at least 2 of the 3 input values is HIGH, THEN
The overall output value is HIGH
ELSE
IF at least 2 of the 3 input values is MEDIUM, THEN
The overall output is MEDIUM
ELSE
The overall output is LOW…

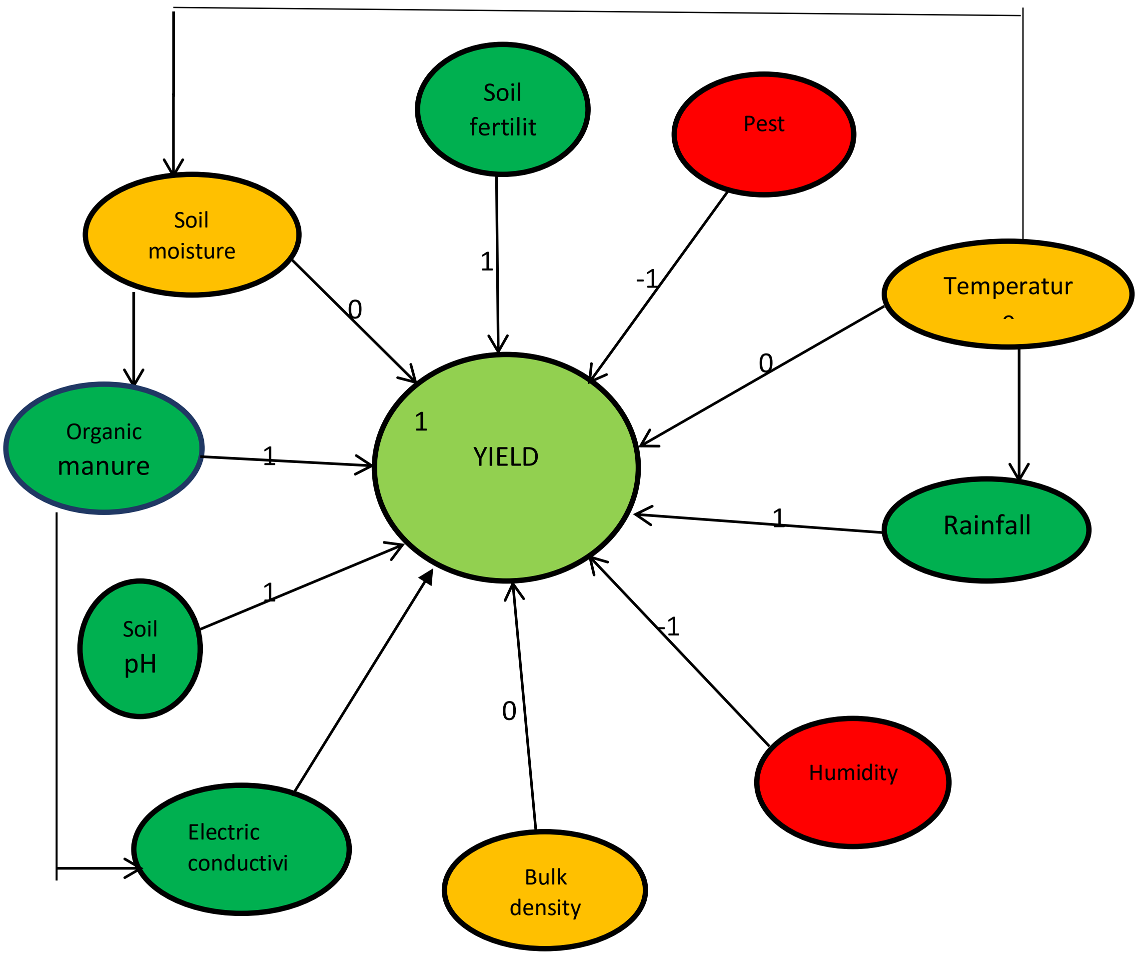

Figure 4.2:Fuzzy Cognitive Map Model for Crop Yield Management

5.0 CONCLUSION

This work is carried out with a view to forecasting crop yielding by using fuzzy cognitive map as the prediction tool. In this work, soil condition was studied and detail analysis of factors that affect crop yielding were carried out. The developed model uses fuzzy cognitive map with if- then rules to accurately predict agricultural products. This research goal was achieved by using the soft computing technique of FCMs to predict the crops and yield variability in a complex process involving different influencing factors such as: soil fertility, soil temperature, humidity, rainfall, soil moisture, organic manure, soil pH, electric conductivity, bulk density and pest. We investigated the efficiency of FCM as a modeling and reasoning technique with respect to a specific precision farming application of crop yield management. Thus, this work can help agricultural scientist, farmers and researchers in determining the yield of agricultural product ahead of time.

REFERENCES

Balakrishnan M & Meena K (2010) ANN model for coconut yield prediction using optimal discriminant plane method at Bay Is- lands. IUP J Comput Sci 4(1):27–34

Gemtos, A. T., Markinos, Ath., Toulios, L., Pateras, D., & Zerva, G. (2004). Precision farming applications in cotton fields of Greece. In 2004 CIGR international conference, Beijing, China, 11–14 October

Kumar SN, Rajeev MS, Vinayan NagvekarDD, Venkitaswamy R, Rao DVR, Boraiah B, Gawankar MS, Dhanapal R, Patil DV& Bai KVK (2009) Trends in weather and yield changes in past in coconut growing areas in India. J Agrometerol 11:15–18

Liu, J., Goering, C. E., & Tian, L. (2001). A neural network for setting target corn yields. Transactions of the ASAE, 44(3), 705–713.

Markinos, A. T., Papageorgiou, E. I., Stylios, C. D., & Gemptos, G. (2007). Introducing fuzzy cognitive maps for decision making in precision agriculture. In Proceedings of sixth European conference on precision agriculture (6ECPA), Skiathos, Greece, 3–6 June 2007, pp. 77–86

Papageorgiou EI, Stylios CD & Groumpos PP (2004) Active Hebbian learning algorithm to train fuzzy cognitive maps. Int J Approx Reason 37(3):219–245

Papageorgiou, E. I., Spyridonos, P., Ravazoula, P., Stylios, C. D., Groumpos, P. P., & Nikiforidis, G. (2006). Advanced soft computing diagnosis method for tumor grading. In Artificial intelligence in medicine (Vol. 36(1), pp. 59–70

Papakostas GA, Poiydoros AS, Koulouritois DE,& Tourassis VD (2011) Training fuzzy cognitive maps by Hebbian learning al- gorithm: a comparative study. IEEE international conference on fuzzy systems, 27–30 June 2011, Taipel, Taiwan

Papageorgiou EI& Salmeron JL (2013) A review of fuzzy cogni- tive maps research during the last decade. IEEE Trans Fuzzy Syst 21(1):66–79

Papageorgiou E (2014) Fuzzy cognitive maps for applied sci- ences and engineering—from fundamentals to extensions and learning algorithms. Intelligent Systems Reference Library 54, Springer 2014. ISBN 978-3-642-39738-7

Peiris TSG, Hansen JW & Zubair L (2008) Use of seasonal climate information to predict coconut production in Sri Lanka. Int J Climatol 28:103–110

Sadiq, R., Kleiner, Y., & Rajani, B. (2006). Interpreting fuzzy cognitive maps (FCMs) using fuzzy measures to evaluate water quality failures in distribution networks. National Research Council of Canada, <http://irc.nrc-cnrc.gc.ca

Stylios, C. D., & Groumpos, P. P. (2004). Modeling fuzzy cognitive maps. IEEE Transactions on Systems, Man and Cybernetics, Part A, 34, 155–162

Zhang H, Shen Z &Miao C (2011) Train fuzzy cognitive maps by gradient residual algorithm. IEEE international conference on fuzzy systems, June 27–30, 2011, Taipel, Taiwan

Author's Brief Profile

Alo Oluwaseun O. (PhD) is a Senior Lecturer in the Department of Information Systems at Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. Her research areas include Algorithms and Complexity Analysis and Information and Communication Science. She can be reached by phone on +2348033896312 and through E-mail ooalo@lautech.edu.ng

Fenwa Deborah O. (PhD) is currently acting head of department of Cyber Security Science at Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. Her research areas include Pattern recognition and Image Analysis. She can be reached by phone on +2348163706286 and through E-mail odfenwa@lautech.edu.ng

Adetunji Abigail B. (PhD) is an Associate Professor in the Department of Computer Science at Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. Her research areas include Information Management and Data Analytics. She can be reached by phone on +2347035344621 and through E-mail abadetunji@lautech.edu.ng