



Application of fuzzy cognitive maps for cotton yield management in precision farming

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ABSTRACT

The management of cotton yield behavior in agricultural areas is a very important task because it influences and specifies the cotton yield production. An efficient knowledge-based approach utilizing the method of fuzzy cognitive maps (FCMs) for characterizing cotton yield behavior is presented in this research work. FCM is a modelling approach based on exploiting knowledge and experience. The novelty of the method is based on the use of the soft computing method of fuzzy cognitive maps to handle experts' knowledge and on the unsupervised learning algorithm for FCMs to assess measurement data and update initial knowledge.

The advent of precision farming generates data which, because of their type and complexity, are not efficiently analyzed by traditional methods. The FCM technique has been proved from the literature efficient and flexible to handle experts' knowledge and through the appropriate learning algorithms can update the initial knowledge. The FCM model developed consists of nodes linked by directed edges, where the nodes represent the main factors in cotton crop production such as texture, organic matter, pH, K, P, Mg, N, Ca, Na and cotton yield, and the directed edges show the cause–effect (weighted) relationships between the soil properties and cotton field.

The proposed method was evaluated for 360 cases measured for three subsequent years (2001, 2003 and 2006) in a 5 ha experimental cotton yield. The proposed FCM model enhanced by the unsupervised nonlinear Hebbian learning algorithm, was achieved a success of 75.55%, 68.86% and 71.32%, respectively for the years referred, in estimating/predicting the yield between two possible categories (“low” and “high”). The main advantage of this approach is the sufficient interpretability and transparency of the proposed FCM model, which make it a convenient consulting tool in describing cotton yield behavior.

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1. Introduction

Fuzzy cognitive maps constitute an attractive modeling technique for complex systems. They belong to the class of soft computing techniques that follow an approach similar to the human reasoning and decision making process. More specifically, fuzzy cognitive maps (FCMs) is a kind of qualitative modeling tool; they provide a simple and straightforward way to model the relationships among different factors. Fuzzy cognitive maps can describe any system using a model with three distinct characteristics: (a) signed causality indicating positive or negative relationship, (b) the strengths of the causal relationships take fuzzy values, and (c) the causal links are dynamic i.e. the effect of a change in one concept/node affect other nodes, which in turn may affect other nodes. The first characteristic implies both the direction and the

nature of the causality. The second characteristic assigns a fuzzy number or linguistic value to reflect the strength of the causality or the degree of association between concepts. Finally, the third characteristic reflects a feedback mechanism that captures the dynamic relationship of all the nodes, which may have temporal implications.

FCMs can be obtained by asking human experts to define the variables of the system and to identify relationships among the variables using ‘if–then’ rules to justify the cause and effect relationship, and infer a linguistic weight for each connection (Stylios & Groumpos, 1999; Papageorgiou & Groumpos, 2005b; Stylios & Groumpos, 2004). FCM consists of nodes which illustrate the variables and the different aspects of the system's behavior. These nodes (concepts) interact with each other showing the dynamics of the model. Human experts who supervise a system and know its behavior under different circumstances develop a FCM model of the system in such a way that their accumulated experience and knowledge are integrated in the causal relationships between factors/characteristics (Stylios & Groumpos, 1999). It is a very

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convenient, simple, and powerful tool through the large number of applications.

In general, changes in the topology or in the weight parameters of the FCM model may result in totally different inference outcomes. FCMs have been used in many different scientific fields for modeling and decision making: political developments (Taber, 1991), electrical circuits (Styblinski & Meyer, 1988), virtual sea world of dolphins, shark and fish (Dickerson & Kosko, 1994), organizational behavior and job satisfaction (Craiger, Weiss, Goodman, & Butler, 1996) and the economic demographics of world nations (Schneider, Kandel, & Chew, 1998). FCMs were combined with data mining techniques to further utilize expert knowledge (Hong & Han, 2002; Lee, Kin, Chung, & Kwon, 2002). Skov and Svenning (2003) combined FCM with a geographic information system in order to apply expert knowledge to predict plant habitat suitability for a forest. Mendoza and Prabhu (2003) used cognitive mapping to examine the linkages and interactions between indicators obtained from a multi-criteria approach to forest management and recently (Mendoza & Prabhu, 2006) presented soft system dynamics models and applications for sustainable forest management.

Moreover, FCMs were used to support the aesthetical analysis of urban areas (Xirogiannis, Stefanou, & Glykas, 2004), and for the management of relationships among organizational members of airline services (Kang & Lee, 2004). Liu and Satur (1999) investigated inference properties of FCMs and they proposed contextual FCMs introducing the object-oriented paradigm for decision support and they applied contextual FCMs to geographical information systems (Liu, 2000). Furthermore, FCMs were used in many disciplines for easy comprehension of complex social systems and for decision making tasks (Miao & Liu, 2000; Papageorgiou & Groumpos, 2005a; Papageorgiou, Stylios, & Groumpos, 2003; Papageorgiou, Stylios, & Groumpos, 2004; Peláez & Bowles, 1996). Furthermore, FCMs using fuzzy measures have been used for evaluation of water quality failures in distribution networks (Sadiq, Kleiner, & Rajani, 2006).

This work aims to apply the soft computing technique of FCMs accompanied with an efficient unsupervised learning algorithm for describing the cotton yield management in precision farming.

Cotton yield prediction in agricultural areas is a crucial factor because it is used to specify cotton crop management. The importance of this factor is more critical when site specific management is considered, due to the existence of many different cases for the same data in the same field. Traditionally crop management has been based on (qualitative) experience but we are trying to put management on a more quantitative basis – and some research has partly succeeded to do this.

The next steps beyond agronomic methods are crop growth models. Many crop growth models have been developed (Fraisie, Sudduth, & Kitchen, 2001; Mathews & Blackmore, 1997; Werner et al., 2000) with questionable value due to large development labor and time. In the area of cotton crop production and management, a crop growth model, named COTMAN, has been developed for cotton crop management (COTMAN, 2007). The COTMAN computer software is used to monitor crop development and makes it easy to enter data and generate the reports used to make management decisions. Furthermore, the GOSSYM/COMAX (McKinion & Wagner, 1994; McKinion et al., 2001) cotton growth model expert system and the GRASS [Grass GIS, 2008] geographic information system have been used to develop a spatial simulation that produces spatially variable outputs.

A large number of approaches, models, algorithms, and statistical tools have been proposed and used for assessing the yield prediction in agriculture. Many authors used simple linear correlations of yield with soil properties but the results varying from field to field and year to year (Drummond, Sudduth, & Birrell, 1995; Gemtos, Markinos, Toullos, Pateras, & Zerva, 2004; Khakural, Robert, & Hug-

gins, 1999). Many other studies, contain complex linear methods like multiple linear regression, were accomplished with similar results (Drummond et al., 1995; Khakural et al., 1999; Kravchenko & Bullock, 2000). Some authors proposed non-linear statistical methods to investigate the yield response (Adams, Cook, Caccetta, & Pringle, 1999; Wendroth, Jurschik, & Nielsen, 1999).

Expert systems and artificial intelligent algorithms are a relatively new subset of nonlinear techniques. They have been proposed in agriculture for decision making and decision support tasks. More specifically, expert systems (Plant & Stave, 1991; Rao, 1992) have been developed and applied in different fields in agriculture to give advices and make management decisions.

In this context many studies have been reported using artificial intelligence techniques and a few of them focalized in the spatial analysis of produced data in precision agriculture. The most of them use artificial neural networks (ANNs) and machine learning algorithms for setting target yields which is one of the problems in precision agriculture (Canteri et al., 2002; Liu, Goering, & Tian, 2001; Miao, Mulla, & Robert, 2006). Schultz, Wieland, and Lutze (2000) summarized the advantages of applying neural networks in agroecological modeling, including the ability of ANN to handle both quantitative and qualitative data, merge information and combine both linear and non-linear responses. Neural networks have been proposed for identifying important factors influencing corn yield and grain quality variability (Miao et al., 2006), for data analysis (Irmak et al., 2006), for prediction crop yield based on soil properties (Drummond, Sudduth, Joshi, Birrell, & Kitchen, 2003), for setting target corn yields (Liu et al., 2001). Shearer et al. (1999) studied a large number of variables, including fertility, satellite imagery, and soil conductivity, for a relatively small number of observations in one site-year of data.

In the case of knowledge-based systems using fuzzy logic techniques only a few studies have been accomplished till today (Ambuel, Colvin, & Karlen, 1994; Khan & Khor, 2004). The first trial to incorporate fuzzy logic techniques to develop yield models for precision farming was made by Ambuel et al. (1994). They examined the potential of using fuzzy logic to develop efficient simulation models that could predict corn yields in central Iowa. The first results on predicted yields compared with the measured ones were preliminary and no further research was done.

A more recent study using fuzzy logic principles was reported by Khan and Khor (2004). He proposed a framework of a fuzzy rule-based cognitive map. The simulation model based on fuzzy logic for the mapping of FCM input state space to the output state space have been presented and implemented for crop yield estimation, considering only four yield factors (pH, potassium, phosphorous and organic matter) related to corn crop yield. The model predicted the variations in corn crop yield with each one of four factors without using real cases or data. The FCM simulations were conducted to study the effects of varying the membership grade of one yield factor, while keeping the other three factors constant at 0.1. These simulations were preliminaries and further work is needed using real measurements.

Therefore, the success of precision agriculture depends on accurate and detailed knowledge of yield potential and crop response to specific conditions. In our previous work (Markinos, Papageorgiou, Stylios, & Gemptos, 2007), the modeling approach of FCMs was introduced for the first time to help make decisions in precision agriculture. An enhanced approach of that work utilizing FCM learning algorithms to handle initial knowledge is accomplished and proposed in the present paper. The use of the soft computing technique of FCMs is suggested from a different standpoint and is enriched with an unsupervised learning algorithm, the nonlinear Hebbian learning (NHL), for estimating the cotton yield for different case studies and characterizing the data into two production yield categories.

The aim of the work reported is to present a methodology that can determine cotton yield behavior in precision farming, based on artificial intelligence (AI) techniques and particularly based on aspects related to knowledge representation. In AI, there are a variety of techniques used for representing knowledge: production rules, semantic networks, frameworks, scripts, statements, logic and fuzzy cognitive maps, among others. In this case, the model was based on fuzzy cognitive maps (FCM). FCM was chosen because of: (a) the nature of the application (estimation of yield trend is a complex process with sufficient interacting parameters and FCMs are suitable for this kind of problem), (b) the user's skills where FCMs exploit experience and accumulated knowledge from experts, (c) ease of use and (d) low time requirement.

2. Theory of FCMs

Cognitive maps were introduced by Axelrod (1976) as a formal way of modeling decision making in social-economic and politic systems. Kosko (1986) modified Axelrod's cognitive maps, with binary values; he suggested the use of fuzzy causal functions taking numbers in $[-1, 1]$ so he introduced the fuzzy cognitive map (FCM). Kosko examined the behavior of FCMs explaining the inference mechanism of FCM. He applied FCMs to model the effect of different policy options using a computational method (Kosko, 1997). The interesting update of concept maps using fuzzy logic is the temporal and causal nature of the FCMs (Kosko, 1992; Lin & Lee, 1996). FCMs express causality over time and allow for causality effects to fluctuate as input values change. Nonlinear feedback can only be modeled in a time-based system. FCMs are intended to model causality, not merely semantic relationships between concepts (Sowa, 1991). By modeling causality over time, FCMs facilitate the exploration of the implications of complex conceptual models, as well as representing them with greater flexibility.

FCMs offer an alternative knowledge fusion scheme (Kosko, 1986; Taber, 1994). An FCM is a fuzzy causal map with closed loops. It consists of nodes and weighted arcs. Nodes of the graph stand for the concepts that are used to describe the behavior of the system and they are connected by signed and weighted interconnections representing the causal relationships that exist between the concepts, as is illustrated in Fig. 1. It has the topology of a fuzzy signed directed graph and dynamics similar to feedback non-linear neural networks.

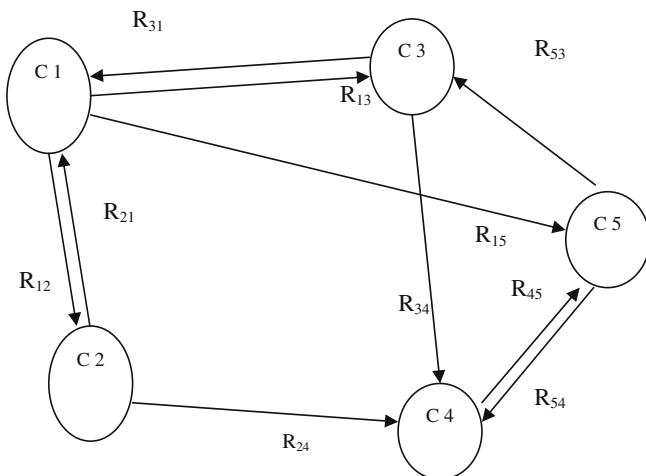


Fig. 1. A simple fuzzy cognitive map.

It should be mentioned that all the values in the graph are fuzzy, so concepts take the values in the range between $[0, 1]$ (i.e. FCM is a bivalent state) and the weights of the interconnections belong to the interval $[-1, 1]$. From simple observation of the graphical representation of FCMs, it becomes clear which concept influences other concepts, showing the interconnection among concepts and it permits thoughts and suggestions for the reconstruction of the graph, i.e. the adding or deleting of an interconnection or a concept.

Fig. 1 illustrates a graphical representation of a FCM consisting of five concepts (C1–C5) and ten weights R_{ji} (cause–effect relationships among the concepts).

FCMs allow experts to express their knowledge by drawing weighted causal digraphs. At first, they identify key domain issues or concepts. Secondly, they identify the causal relationships among these concepts and thirdly, they estimate causal relationships strengths. The achieved graph (FCM) shows not only the components and their relations but also the strengths. All experts are asked to determine the relevant factors in a brain storm meeting. Thus, the constructed FCM will represent the knowledge and experience of all related experts (Stylios & Groumpos, 2004). FCMs can be produced by experts manually or generated by other source of information computationally (manual FCMs and automated FCMs).

The cause and effect interconnection between two concepts C_j and C_i is described with the weight R_{ji} , taking a value in the range -1 to 1 . There are three possible types of causal relationships between concepts:

- $R_{ji} > 0$ which indicates positive causality between concepts C_j and C_i . That is, an increase (decrease) in the value of C_j leads to an increase (decrease) in the value of C_i .
- $R_{ji} < 0$ which indicates negative causality between concepts C_j and C_i . That is, an increase (decrease) in the value of C_j leads to a decrease (increase) in the value of C_i .
- $R_{ji} = 0$ which indicates no relationship between C_j and C_i .

The graphical representation of a FCM has a mathematical formulation. Values of concepts are fuzzy and arise from the transformation of the real values of the corresponding variables for each concept, and also the values for the weights of the interconnections among concepts are fuzzy. Then, in order to calculate the values of the concepts, the following calculation rule is used:

$$A_i^{(k+1)} = f \left(A_i^{(k)} + \sum_{j \neq i}^N A_j^{(k)} \cdot R_{ji} \right) \quad (1)$$

where $A_i^{(k+1)}$ is the value of concept C_i at simulation step $k+1$, $A_j^{(k)}$ is the value of concept C_j at simulation step k , R_{ji} is the weight of the interconnection from concept C_j to concept C_i and f is a sigmoid threshold function:

$$f = \frac{1}{1 + e^{-\lambda x}} \quad (2)$$

where $\lambda > 0$ is a parameter that determines its steepness. In our approach, the value $\lambda = 1$ has been used. This function is selected since the values A_i lie within $[0, 1]$.

The value A_i of the concept C_i expresses the degree of its corresponding physical value. At each simulation step, the value A_i of a concept C_i is calculated by computing the influence of other concepts C_j 's on the specific concept C_i following the corresponding mathematical formulation.

Through iteratively multiplying the previous state vector by the connection matrix, using standard matrix multiplication, new state vectors are computed showing the effect of the activated concepts (Peláez & Bowles, 1996). After every multiplication, the values of

the state vector are normalized by a non-linear function that allows the vector elements to take a value within a predetermined set of values. Commonly, the functions used allow the variables to take values in $\{0, 1\}$, in $\{-1, 0, 1\}$, or in $[-1, 1]$ (Tsadiras & Margaritis, 1997). FCM inference goes on by non-linear spreading activation, which implies that the inference or prediction is a temporal sequence of events or reverberating limit cycle (Kosko, 1992). Iteration terminates when it reaches an equilibrium state and stops yielding new data, or when a prearranged iteration count has been reached (Taber, 1991).

2.1. Constructing FCMs

The development and construction method of FCM is of great importance for its potential to sufficiently model a system. Proposed methods are dependent on the group of experts who operate, monitor, supervise the system and they know its behaviour. This methodology extracts the knowledge from the experts and exploits their experience of the system's model and behaviour.

The number and kind of concepts are determined by a group of experts that comprise the FCM model. An expert from his/her experience knows the main factors that describe the behaviour of the system; each of these factors is represented by one concept of the FCM. Experts know which elements of the systems influence other elements; they determine the negative or positive effect of one concept on the others, with a fuzzy degree of causation for the corresponding concepts. In this way, an expert transforms his/her knowledge in a dynamic weighted graph, the FCM. Following the developing methodology, experts are forced to think about and then describe the existing relationship between the concepts and thus justify their suggestions. Each expert, indeed, determines the influence of one concept on another as "negative" or "positive" and then evaluates the degree of influence using a linguistic variable, such as "strong influence", "medium influence", "weak influence", etc.

The causal inter-relationships among concepts are usually declared using the variable *Influence* which is interpreted as a linguistic variable taking values in the universe $U = [-1, 1]$. Its term set $T(\text{influence})$ is suggested to comprise seven variables. Using seven linguistic variables, an expert can describe in detail the influence of one concept on another and can discern between different degrees of influence. The seven variables used here are: $T(\text{influence}) = \{\text{very very low, very low, low, medium, high, very high, and very very high}\}$. The corresponding membership functions for these terms are shown in Fig. 2 and they are: $\mu_{vvl}, \mu_{vl}, \mu_l, \mu_m, \mu_h, \mu_{vh},$ and μ_{vvh} .

The main concepts that represent the model of the system are defined by experts; they describe the structure and the interconnections of the network using fuzzy conditional statements. The fuzzy IF-THEN rules that experts use to describe the relationship

among concepts assume the following form, where **A** and **B** are linguistic variables:

*IF value of concept C_i is **A** THEN value of concept C_j is **B**
and thus the linguistic weight e_{ij} is **C***

where **A**, **B**, **C** are linguistic variables (determined from the previous membership functions) taking values in the range $[0, 1]$.

Thus, each interconnection is described by an expert with a fuzzy linguistic variable from the determined set, which associates the relationship between the two concepts and determines the grade of causality between the two concepts. Then, the linguistic variables **C** proposed by the experts for each interconnection are aggregated using the SUM method and so an overall linguistic weight is produced which is defuzzified with the Centre of Area method and finally a numerical weight for R_{ij} is calculated. Using this method, all the weights of the FCM model are inferred.

2.2. Nonlinear Hebbian learning algorithm for FCMs

In this sub-section the Nonlinear Hebbian Learning (NHL) Algorithm which was proposed to train FCM is described. The NHL algorithm is used to overcome inadequate knowledge of experts and/or non-acceptable FCM simulation results (Papageorgiou et al., 2003; Papageorgiou & Groumpos, 2005). The weight adaptation procedure is based on the Hebbian Learning rule for non-linear units (Oja, Ogawa, & Wangiwattana, 1991). The nonlinear Hebbian-type rule for ANNs learning have been adapted and modified for the FCM case, and there was proposed the nonlinear Hebbian learning (NHL) algorithm (Papageorgiou & Groumpos, 2005).

Through the NHL algorithm all the concepts in FCM model are triggering synchronously at each iteration step. During this triggering process the weight w_{ji} of the causal interconnection of the related concepts is updated and the modified weight $w_{ji}^{(k)}$ is calculated for iteration k .

The Eq. (1) is updated to Eq. (3) where the value $A_i^{(k+1)}$ of C_i concept, at simulation step $k + 1$, is calculated, computing the influence of interconnected concepts with values A_j to the specific concept C_i due to modified weights $w_{ji}^{(k)}$ at simulation step k :

$$A_i^{(k+1)} = f \left(A_i^{(k)} + \sum_{j=1, j \neq i}^N A_j^{(k)} \cdot w_{ji}^{(k)} \right) \quad (3)$$

Furthermore, during the development phase of FCM, experts select the Decision Output Concepts (DOCs) and they also define the initial stimulators (factor concepts) or interior concepts (selector-concepts) of the system. The distinction of FCM concepts as inputs, intermediates and outputs is determined by the group of experts

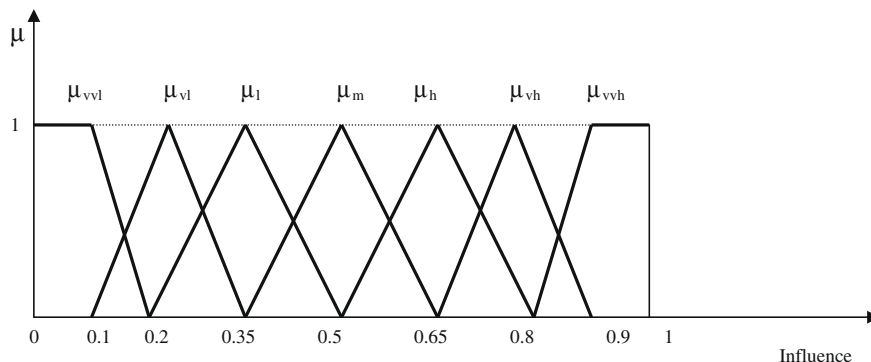


Fig. 2. The seven membership functions corresponding to each one of the seven linguistic variables.

for each specific problem. The DOCs stand for the outputs of the system that interest us, and we want to estimate their values, which represent the final state of the system.

Taking the advantage of the general nonlinear Hebbian-type learning rule for NNs, we introduce the mathematical formalism incorporating this learning rule for FCMs, a learning rate parameter and the determination of input and output concepts. This algorithm relates the values of concepts and values of weights in the FCM model.

The proposed learning rule Papageorgiou & Groumpos, 2005 has the general mathematical form:

$$\Delta w_{ji} = \eta_k A_i^{(k-1)} A_j^{(k-1)} - w_{ji}^{(k-1)} (A_i^{(k-1)})^2 \quad (4)$$

where the coefficient η_k is a very small positive scalar factor called learning parameter and is determined using experimental trial and error method in order to converge fast the simulation process. $A_j^{(k)}$ is the value of concept C_j , which at next simulation step, $k + 1$, triggers the interconnected concepts.

This simple rule states that if $A_i^{(k)}$ is the value of concept C_i at simulation step k , and A_j is the value of the concept C_j that triggers the concept C_i , the corresponding weight from concept C_j towards the concept C_i increases proportional to their product multiplied with the learning rate parameter minus the weight decay at simulation step $k - 1$, that is multiplied by the value A_j of triggering concept C_j . All the FCM concepts are triggering at the same iteration step and their values are updated synchronously.

Eq. (4) takes the following form of nonlinear weight adaptation algorithm, if we introduce the γ as weight decay parameter:

$$w_{ji}^{(k)} = \gamma \cdot w_{ji}^{(k-1)} + \eta_k A_i^{(k-1)} (A_j^{(k-1)} - \text{sgn}(w_{ji}^{(k-1)}) w_{ji}^{(k-1)} A_i^{(k-1)}) \quad (5)$$

where the η_k is the learning rate parameter and γ is the weight decay parameter.

The value of each concept of FCM is updated, through the Eq. (3) where the value of weight $w_{ji}^{(k)}$ is calculated using Eq. (5).

Only the initially non-zero weights suggested by experts are updated for each iteration step through the NHL algorithm. All the

other weights of weight matrix $\mathbf{W}$ remain equal to zero, which is their initial value.

Also, two termination conditions were proposed for the termination of the learning algorithm. One termination condition is the minimization of function F_1 . The termination function F_1 that has been proposed for the NHL examines the values of Decision Output Concepts (DOCs). It is supposed that for each DOC_i , experts have defined a target value T_i . This target value can be either the desired value when DOC_i stand for a concept, which has to take a value or the mean value when DOC_i stand for a concept whose value has to belong to an interval. Thus, the function F_1 is defined as:

$$F_1 = \sqrt{\sum_{i=1}^l (DOC_i - T_i)^2} \quad (6)$$

where l is the number of DOCs.

The second termination condition is the minimization of the variation between two subsequent values of DOCs, represented by equation:

$$F_2 = |DOC_i^{(k+1)} - DOC_i^{(k)}| < e \quad (7)$$

This termination condition helps to terminate the iterative process of the learning algorithm. The term e (equal to 0.001 to be satisfying the termination), is a tolerance level keeping the variation of values of DOC(s) as low as possible.

Through this training process and when both the termination conditions are met, the final weight matrix $\mathbf{W}_{NHL}$ of FCM is derived.

After a great number of experiments and implementation the NHL algorithm in different domains, the upper and lower bounds for the learning rate parameters γ and η were determined (Papageorgiou & Groumpos, 2005). The flowchart of the proposed NHL procedure implemented in FCMs is given in Fig. 3. It is mentioned that if the learning procedure repeated for over 1000 iteration steps without converge then it stops and experts are asked to reconstruct the FCM.

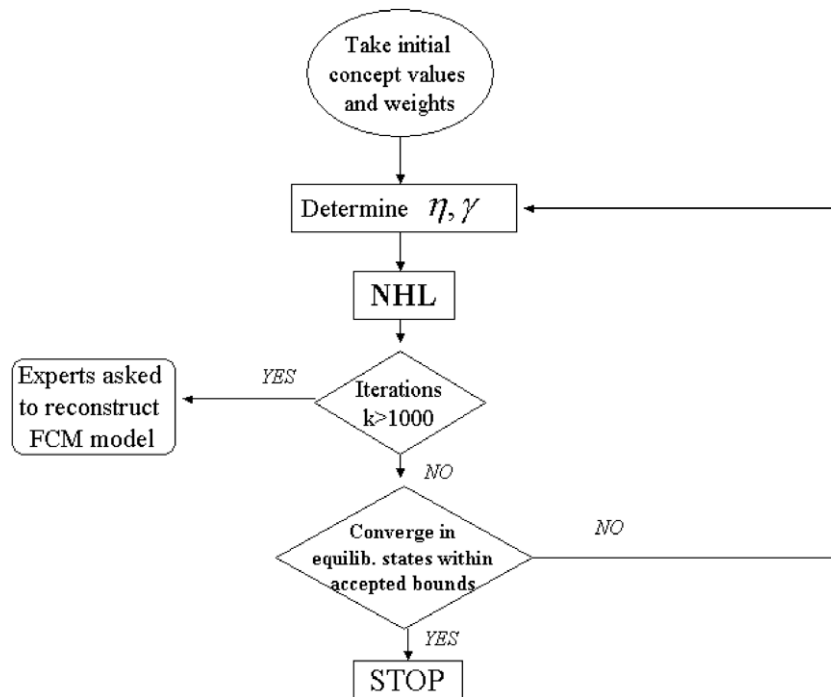


Fig. 3. The flowchart of NHL algorithm.

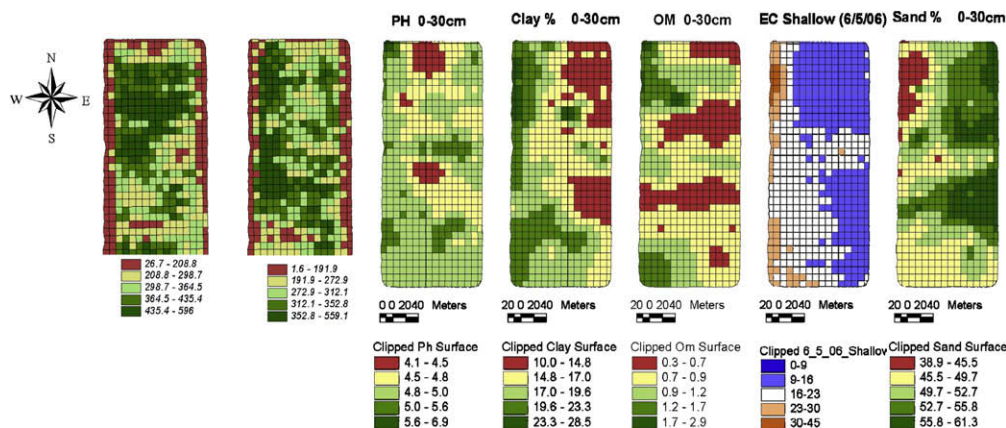


Fig. 4. Two of the yield maps (years 2001 and 2003) and some of the soil properties maps.

3. Materials and methods

In 2001, an experiment was established in a 5 ha field at Myrina, Karditsa prefecture, Central Greece. During the last 6 years, the field was cultivated with cotton (*Gossypium hirsutum* L.) and the Celia cultivar. It was managed using spatially uniform applications and a series of measurements were made each year.

Yield mapping was performed for the years 2001–06 using a FarmScan™ yield monitor installed on a two row John Deere™ cotton picker (Gemtos et al., 2004). After harvesting of the field was completed, a calibration procedure was performed to improve the yield estimation (Markinos et al., 2004).

In February 2002, a 16 × 26 m grid was formed in the north part of the field (4.3 ha). Overall, 114 soil samples were taken at the grid points at 0–30 cm depth. The samples were analyzed for texture, N, P, K, pH, Mg, Ca, Na and organic matter.

In May 2006, a VERIS machine was used to measure the apparent soil EC_a at depths 0–0.30 and 0–0.90 m (Lund, Christy, & Drummond, 1999) from which maps were generated. The machine was pulled through the field at a speed of approximately 7 km/h at a track spacing of 4 m. Data were recorded every 1 s.

The SStoolbox™ 3.61 software was used to store, represent, filter and analyze the acquired field data (SStoolbox, 2004). All the collected data were interpolated in order to produce a map (4.3 ha) on a 10 × 10 m grid size that corresponds to a reliable field management unit (cell). The interpolation method of inverse distance was used for yield and EC due to dense data sampling, while kriging was used for the soil properties maps of sparse spatial sampling-grid (SStoolbox, 2004) (Fig. 4).

Data from 20 m strips around the field near the edges were filtered and removed to avoid machinery compacted headlands with lower yields. The data of every cell (10 × 10 m) of filtered maps represent the data to be used as inputs in the FCM model simulations with the yield from each year as output. Every cell of each input map linked to a scalar value in the GIS database. Each particular cell corresponding to the same spatial point represents a vector of scalar values of respective measured soil parameters. The last value in the vector represents the yield at this field point. Every vector constitutes a record in the database extracted from GIS.

The FCM model has been developed based on a raster data GIS approach, i.e. the data are stored in a two-dimensional matrix that represents the spatial distribution of every factor in the field. Each cell of the matrix corresponds to an area of 10 × 10 m, which is the spatial resolution of the yield data model. The data of every cell of

filtered maps represent the data that will be used as input variables in the proposed FCM model. Each one vector of the data record represents the initial concept values of the proposed FCM model that interact through the FCM simulation process till an equilibrium point or decision is reached. Each causal node or factor of the FCM model represents a discrete layer or raster map in the yield data model.

The FCM model was developed by experts (one experienced cotton farmer and two experienced soil scientists) and the measurement data were used to be categorized by the FCM tool into two yield production categories. These data were the result of three years of measurements (2001, 2003 and 2006) at the same cotton field in Central Greece (Gemtos et al., 2004; Markinos et al., 2004).

4. Fuzzy cognitive map model for describing cotton yield

To construct the FCM model for describing spatial variation in cotton yield, three experts described below were used. The experts designed the FCM model following the developing methodology described in the previous section. The three experts were one experienced cotton farmer and two experienced soil scientists, one from Technological Educational Institute of Larissa, Greece and the other from the Laboratory of Regional Soil Analysis and Agricultural Applications of Larissa, Greece.

The three experts stated that there are eleven main factors – variables (which represent soil properties) used to determine cotton yield (see Table 1). These eleven are the main factors determining cotton yield and are well documented in the literature (Galanopoulou, 2002).

The concepts of FCM and their ranges have been described qualitatively by experts and have been converted into fuzzy sets with corresponding membership functions, given in Table 2. Then, the initial values of concepts were transformed into the range [0, 1] with quantification based on fuzzy sets theory (Jang, Sun, & Mizutani, 1997).

The set of linguistic variables that every concept can take are depicted in Table 2 and the corresponding membership functions for the eleven soil parameters and cotton yield are illustrated in Fig. 5.

Then, experts were asked to describe the degree of influence between the concepts and they determined their inter-relationships using the “IF–THEN” rules previously presented to infer a linguistic variable (weight), representing the cause and effect relationship between every pair of concepts. Three linguistic variables have been proposed by the three experts for each intercon-

Table 1

Concepts of the FCM model.

Concepts	Description: soil factors measured over 0–300 mm soil depth	Type and number of scaled values
C1: ShallowEC	Soil shallow electrical conductivity Veris (mS/m)	Five fuzzy
C2: Mg	Magnesium (ppm)	Five fuzzy
C3: Ca	The measured calcium in the soil in depth 0–30 cm (ppm)	Five fuzzy
C4: Na	The measured Na (Sodium) in the soil in depth 0–30 cm (ppm)	Five fuzzy
C5: K	The measured Potassium in the soil in depth 0–30 cm (ppm)	Five fuzzy
C6: P	The measured Phosphorus in the soil in depth 0–30 cm (ppm)	Five fuzzy
C7: N	The measured NO ₃ in the soil profile of 0–30 cm (ppm)	Five fuzzy
C8: OM	The % Organic matter content in soil profile in depth 0–30 cm	Three fuzzy
C9: Ph	The pH of the soil in depth 0–30 cm	Seven fuzzy
C10: Sand	The % of the sand in the soil samples in depth 0–30 cm	Four fuzzy
C11: Clay	The percentage % of the clay in samples in depth 0–30 cm	Three fuzzy
C12: Yield	Seed cotton yield from 1st picking measured by yield monitor (t/ha)	Three fuzzy

Table 2

Qualitative description (type) of each one of FCM concepts values.

C1: ShallowEC (mS/m)		C2: Mg (ppm)		C3: Ca (ppm)		C4: Na (ppm)	
Five fuzzy		Five fuzzy		Five fuzzy		Five fuzzy	
0–10	Very low	<60	Very low	<400	Very low	<25	Very low
10–20	Low	60–180	Low	400–1000	Low	25–70	Low
20–30	Medium	181–360	Medium	1001–2000	Medium	71–160	Medium
30–40	High	361–950	High	2001–4000	High	161–460	High
>40	Very high	>950	Very high	>4000	Very high	>460	Very high
C5: K (ppm)		C6: P (ppm)		C7: N (ppm)		C8: OM (ppm)	
Five fuzzy		Five fuzzy		Five fuzzy		Three fuzzy	
<40	Very low	<5	Very low	<3	Very low	<1.0	Low
40–120	Low	5–15	Low	3–10	Low	1.0–2.0	Medium
121–240	Medium	16–25	Medium	11–20	Medium	>2.0	High
241–470	High	26–45	High	21–40	High		
>470	Very high	>45	Very high	>40	Very high		
C9: Ph		C10: Sand (%)		C11: Clay (%)		C12: Yield (tons/ha)	
Seven fuzzy		Four fuzzy		Three fuzzy		Three fuzzy	
<4.5	Very low	<20	Low	<15	Low	< 2.5	Low
4.6–5.5	Low	20–70	Medium	15–37	Medium texture	2.5–3.5	Medium
5.6–6.5	Sl. Low	71–80	High	>37	High	>3.5	High
6.6–7.5	Neutral	>80	Very high				
7.6–8.5	Sl. High						
8.6–9.5	High						
>9.5	Very high						

nection. These three linguistic weights are aggregated using the SUM method and so an overall linguistic weight is produced which is defuzzified with the Centre of Gravity method and finally a numerical weight for R_{ij} is calculated. The advantage of this methodology is that experts do not have to describe the causality relationships using numerical values, but rather to describe qualitatively the degree of causality between concepts. The fuzzy rule for each interconnection is evaluated using fuzzy reasoning and the inferred fuzzy weight is defuzzified using the Center of Gravity defuzzification method. Thus the initial weight matrix of the FCM is assigned.

The three experts suggested that the degree of influence between concepts was described by a linguistic variable taking a value in [0, 1] and its fuzzy set defined in previous section (shown in Fig. 2). It is noticeable that these membership functions have a finer distinction between grades in the lowest and highest end of the influence scale.

Two examples for the specific problem of yield trend description in cotton are given:

IF a small change occurs in the value of concept C_8 (organic matter) **THEN a small** change in the value of concept C_{12} (cotton yield) is caused.

This means that: the influence from concept C_8 – C_{12} is **low**.

IF a high change occurs in the value of concept C_1 (ShallowEC) **THEN a very high** change in the value of concept C_{12} (cotton yield) is caused.

This means that: the influence from concept C_1 – C_{12} is **very high**.

The three experts were asked to describe the degree of influence from one concept to another using “IF–THEN” rules among factor concepts and yield. All fuzzy rules were pooled by experts for each interconnection of FCM and were gathered in Table 3. In this table, only the different suggestions of the second and third expert were presented according to the first expert fuzzy rules.

These fuzzy rules for each causal relationship were aggregated using the approach described by Stylios and Groumpos (2004) and so an overall linguistic rule was produced from which through the SUM fuzzy inference method, a numerical weight for R_{ij} was calculated (see Eq. (8)). Using this, the weights of the FCM model were inferred and the FCM was developed (see Fig. 7).

To illustrate how numerical values of weights have been produced, the following example is given. The three experts have described the interconnection between concept C_5 (Potassium) and concept C_{12} (yield) using the following rules:

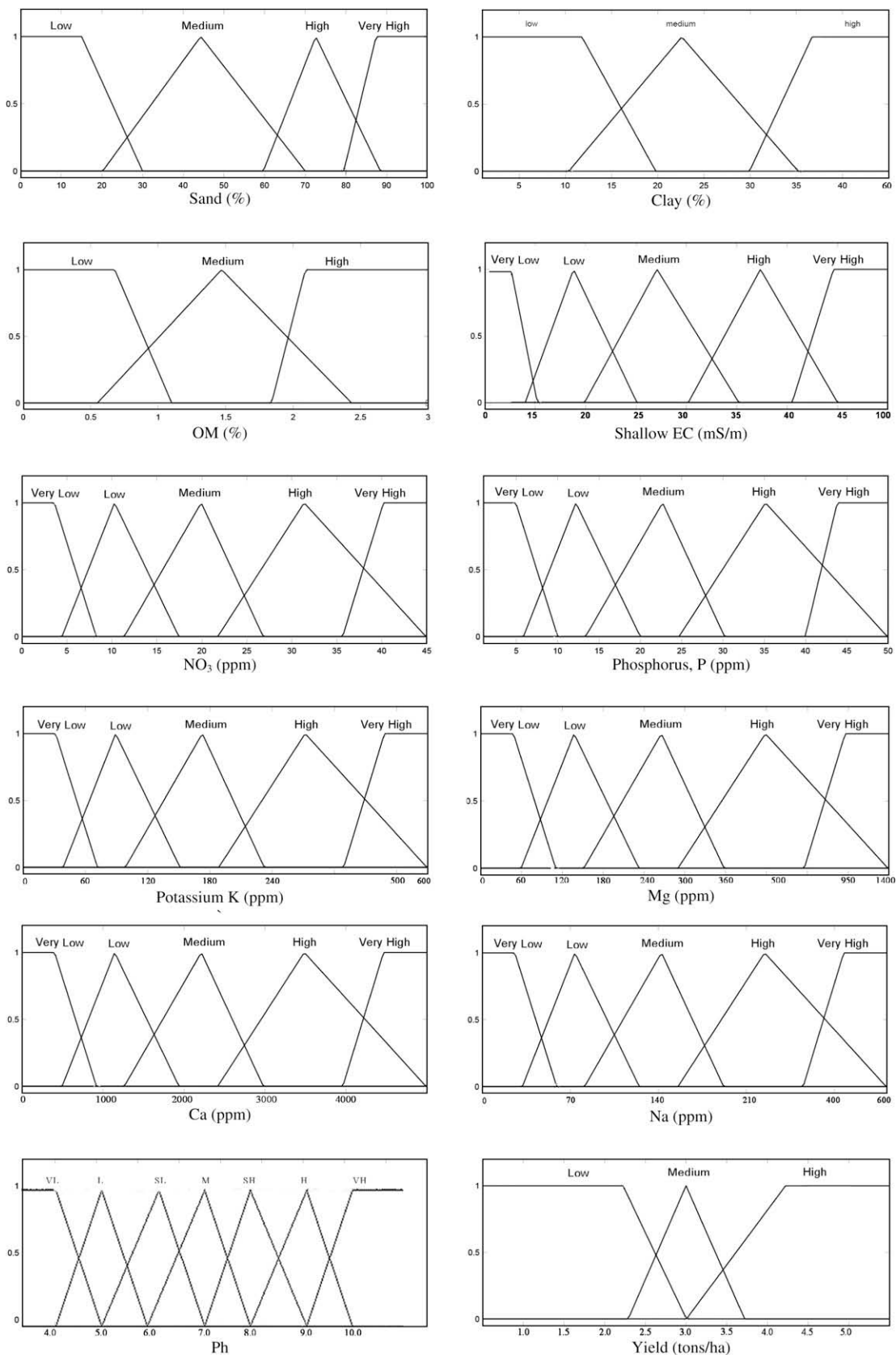


Fig. 5. Membership functions for ShallowEC, Mg, Ca, Na, K, P, N, OM, Ph, Sand, Clay and Yield.

Table 3

Fuzzy rules relating yield factors to yield.

Factor concept	First expert	Second expert (only where different)	Third expert (only where different)
C ₁ : Shallow EC (EC)	IF EC is VL Then Y is L	IF EC is L Then Y is L	IF EC is L Then Y is L
	IF EC is L Then Y is M		
	IF EC is M Then Y is M		
	IF EC is H Then Y is M		IF EC is H Then Y is H
C ₂ : Magnesium (Mg)	IF EC is VH Then Y is H	IF Mg is H Then Y is M	
	IF Mg is VL Then Y is L		IF Mg is L Then Y is M
	IF Mg is L Then Y is L		
	IF Mg is M Then Y is H		
	IF Mg is H Then Y is H		IF Mg is H Then Y is M
	IF Mg is VH Then Y is M		
C ₃ : Calcium (Ca)	IF Ca is VL Then Y is L	IF Ca is M Then Y is M	
	IF Ca is L Then Y is L		
	IF Ca is M Then Y is H		
	IF Ca is H Then Y is M		IF Ca is H Then Y is L
	IF Ca is VH Then Y is M		IF Ca is VH Then Y is L
C ₄ : Sodium (Na)	IF Na is VL Then Y is H		IF Na is VL Then Y is M
	IF Na is L Then Y is M		
	IF Na is M Then Y is L		
	IF Na is H Then Y is L		
	IF Na is VH Then Y is L		
C ₅ : Potassium (K)	IF K is VL Then Y is VL	IF K is VH Then Y is M	
	IF K is L Then Y is L		
	IF K is M Then Y is M		
	IF K is H Then Y is M		
	IF K is VH Then Y is H		IF K is VH Then Y is M
C ₆ : Phosphorous (P)	IF P is VL Then Y is L		
	IF P is L Then Y is L		
	IF P is M Then Y is M		IF P is H Then Y is H
	IF P is H Then Y is M		IF P is VH Then Y is M
C ₇ : Nitrogen (N)	IF P is VH Then Y is H		
	IF N is VL Then Y is L		
	IF N is L Then Y is L		
	IF N is M Then Y is M		
	IF N is H Then Y is H		IF N is H Then Y is M
C ₈ : Organic matter (OM)	IF N is VH Then Y is H		IF N is VH Then Y is M
	IF OM is L Then Y is L		
	IF OM is M Then Y is M		
	IF OM is H Then Y is M		IF OM is H Then Y is H
C ₉ : Ph	IF OM is H Then Y is M	IF Ph is H Then Y is L	
	IF Ph is VL Then Y is L		
	IF Ph is L Then Y is L		
	IF Ph is SL Then Y is M		
	IF Ph is M Then Y is M		
	IF Ph is SH Then Y is H		
C ₁₀ : Sand (S)	IF Ph is H Then Y is M	IF S is M Then Y is M	
	IF Ph is VH Then Y is L		
	IF S is L Then Y is M		IF S is L Then Y is H
	IF S is M Then Y is H		
C ₁₁ : Clay (Cl)	IF S is H Then Y is L	IF Cl is H Then Y is M	
	IF S is VH Then Y is L		
	IF Cl is L Then Y is L		
	IF Cl is M Then Y is M		IF Cl is H Then Y is M

1st Expert

IF value of concept C₅ is **med** THEN value of concept C₁₂ is **med**
Infer: The influence from concept C₅ towards concept C₁₂ is **med**

2nd Expert

IF value of concept C₅ is **med** THEN value of concept C₁₂ is **high**
Infer: The influence from concept C₅ towards concept C₁₂ is **high**

3rd Expert:

IF value of concept C₅ is **high** THEN value of concept C₁₂ is **very high**
Infer: The influence from concept C₅ towards concept C₁₂ is **very high**

Fig. 6 illustrates the three suggested linguistic variables for this particular problem example.

These linguistic variables (med, high and very high) were summed and an overall linguistic weight was produced (also in Fig. 6) which, through the defuzzification method of Centre of Gravity (COG), was transformed into the numerical value of $R_{5-12} = 0.65$ (weight value from concept C₅ towards concept C₁₂).

The same approach was used to determine all the weights of the FCM model. A weight matrix $R^{initial}$ gathering the initially suggested weights of all the interconnections among the concepts of the FCM model was produced.

$$R^{initial} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.25 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.4 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.4 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.7 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.6 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.3 \\ 0.4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.4 \\ 0 & 0 & 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 \\ -0.25 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -0.6 \\ 0.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (8)$$

The developed FCM model is presented in Fig. 7.

The procedure referred to is based on the determination of the value of output concept “Yield” that represents the percentage of cotton yield from the 1st picking measured with the yield monitor. The concept values correspond to the soil factor values measured over a depth of 0–30 cm.

5. Results and discussion

The initial values of concepts are transformed into the range [0, 1], with quantification based on fuzzy sets theory, for the simulation of FCM (Jang et al., 1997).

The FCM simulates through Eq. (1) and the new values for concepts are calculated till the FCM tool for describing cotton yield trend reaches an equilibrium point (steady state for the specific set of concepts) where the values of concepts do not change any more from their previous ones. After these limited number of interactions for the FCM convergence, the value A_{12} of concept C₁₂ represents the category or the classification degree for the case of cotton yield.

In this point, it is essential to refer that the three experts also determined a threshold value equal to 0.85 to discriminate two

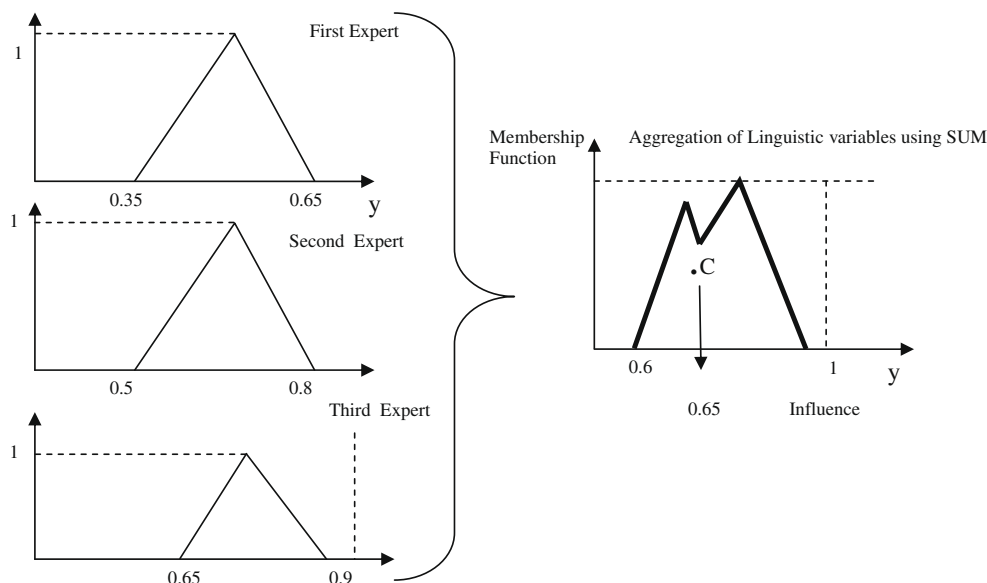


Fig. 6. Aggregation of three linguistic variables using the SUM technique. Point C is the numerical weight after defuzzification using the CoG method.

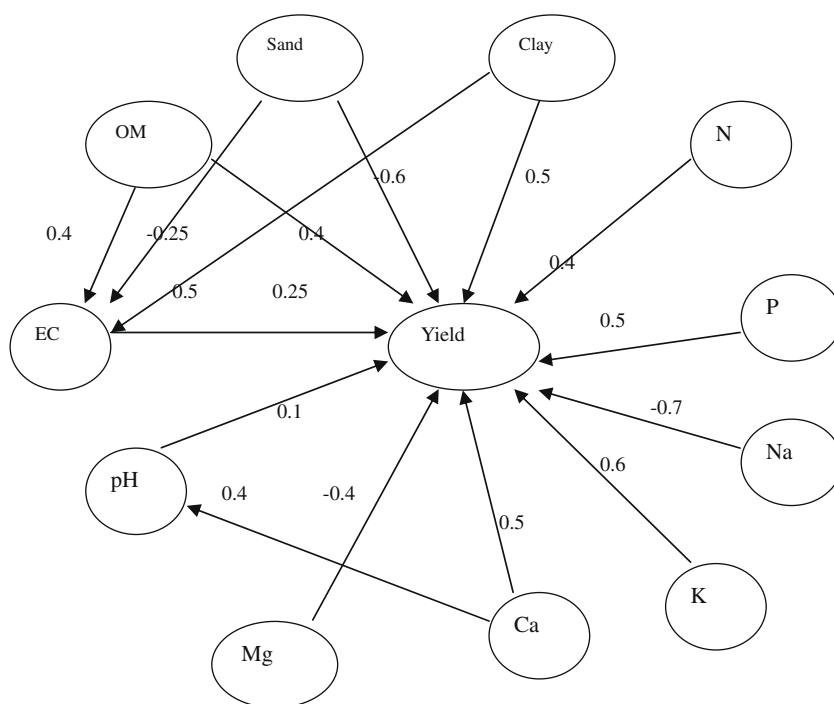


Fig. 7. The FCM model for describing the final cotton yield.

different categories for the seed cotton yield production. More specifically, the experts suggested that yield value higher than 85% of desired cotton production could be considered as high cotton production. In our approach this was translated as follows:

If the estimated “yield” value (A_{12}) is less than 0.85 ($A_{12} \leq 0.85$), which means that the yield production is less than the 85% of desired cotton production, then “yield” is categorized as “low”. If the estimated “yield” value (A_{12}) is higher than 0.85 ($A_{12} > 0.85$), then “yield” is categorized as “high”.

Three different cases have been examined to evaluate the proposed methodology based on FCMs for determining category of cotton production.

First case: In this case, the initial fuzzy values of the concepts which correspond to low yield production (as they have been measured and converted to the corresponding fuzzy sets), are the following:

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Very low	high	med	low	med	med	low	low	Low	med	high

The following vector is used for the FCM simulation process and describes the numerical values of initial concepts after their quantification through fuzzy logic:

$$A^1 = [0.1 \quad 0.75 \quad 0.7 \quad 0.4 \quad 0.5 \quad 0.5 \quad 0.2 \quad 0 \quad 0.3 \quad 0.5 \quad 0.7 \quad 0]$$

These values represent the real data of the physical process and the initial value of yield production is set equal to zero. These values are used in Eq. (1) to calculate the equilibrium region of the process. After 11 iteration steps, the FCM reaches an equilibrium state, where the values do not change any more from their previous ones. This state is:

$$A^{\text{fin-1}} = [0.7201 \quad 0.7500 \quad 0.7548 \quad 0.4000 \quad 0.5000 \quad 0.5000 \quad 0.2000 \quad 0 \quad 0.7390 \quad 0.5000 \quad 0.7000 \quad 0.8226]$$

C_{12} is 0.8226, which means that, in this region, the yield is less than the threshold value 0.85 which has been considered by experts to discriminate two different categories for the yield based on the 85% of the acceptable seed cotton production. Actually, for this case, the measured yield production was “low” as the initial values corresponded to low cotton production, so that the derived result of the FCM model is the expected one according to the real measurements (“low” yield).

Fig. 8 depicts the subsequent values of calculated concepts for every simulation step. It is observed that the final value of concept

Second case: Here the initial measured fuzzy values of the concepts are the following:

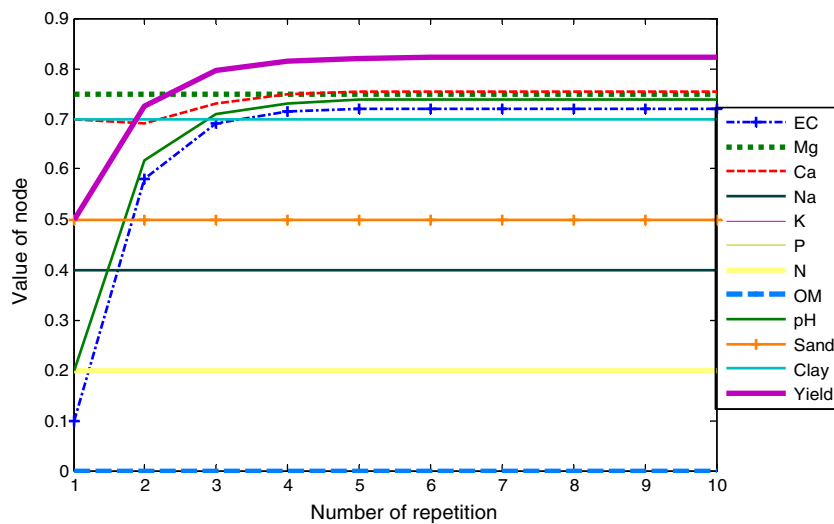


Fig. 8. Subsequent values of concepts for first case till convergence.

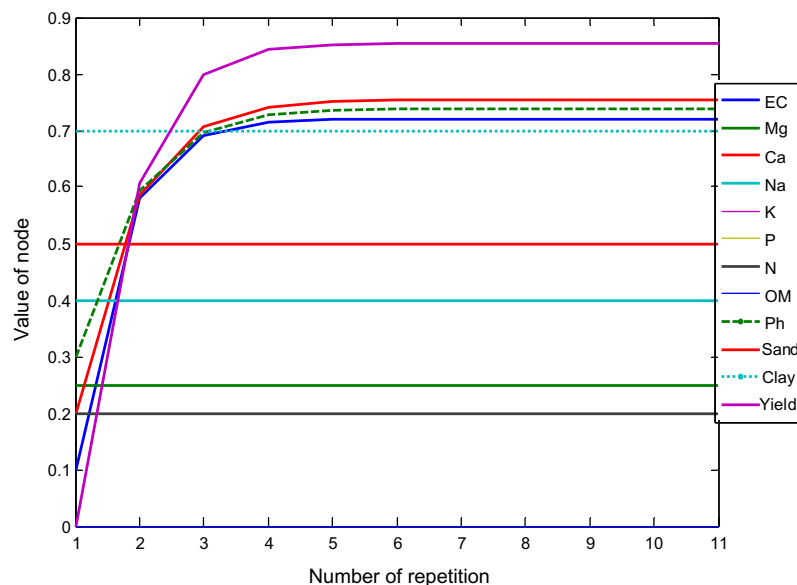


Fig. 9. Subsequent values of concepts for second case till convergence.

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
Very low	low	med	low	med	med	low	low	low	med	high

The initial values of concepts for this case are determined in the following vector:

$$A^2 = [0.1 \quad 0.25 \quad 0.2 \quad 0.4 \quad 0.5 \quad 0.5 \quad 0.2 \quad 0 \quad 0.3 \quad 0.5 \quad 0.7 \quad 0]$$

These values with the corresponding FCM weights are used in Eq. (1) to calculate the equilibrium region of the process. After 12 iteration steps, the equilibrium region is reached:

$$A^{\text{fin-2}} = [0.7201 \quad 0.2500 \quad 0.7548 \quad 0.400 \quad 0.500 \quad 0.5000 \quad 0.2000 \quad 0.0739 \quad 0.5000 \quad 0.7000 \quad 0.8539]$$

Fig. 9 gives the subsequent values of calculated concepts. In this case, it is observed that the value of concept C_{12} ("yield") in final state is 0.8539, which means that the yield is "high" according to the previous referred threshold value of 0.85. This means that the estimated result is the accepted one.

Third case: For this case, the initial fuzzy values of the concepts have been selected from real measurements and have been corresponded to high yield production:

C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
low	high	med	low	med	med	low	med	med	med	high

The initial vector for the concept values is:

$$A^3 = [0.4 \quad 0.75 \quad 0.7 \quad 0.4 \quad 0.5 \quad 0.5 \quad 0.2 \quad 1 \quad 0.5 \quad 0.5 \quad 0.7 \quad 0]$$

This vector represents the real data of the physical process. Then, using Eq. (1), the FCM simulates and after 12 iteration steps, the equilibrium region is reached in the following vector:

$$A^{\text{fin-3}} = [0.8073 \quad 0.7500 \quad 0.7548 \quad 0.400 \quad 0.5000 \quad 0.5000 \quad 0.2000 \quad 0 \quad 0.739 \quad 0.5000 \quad 0.7000 \quad 0.8824]$$

Fig. 10 gives the subsequent values of calculated concepts. Actually, for this case, the measured yield production was "high". It is observed that the calculated value of concept C_{12} in final equilibrium point is 0.8824, which means that the yield is higher than the 0.85 so that it can be considered as "high" yield. The derived result is the expected one according to the real measurements for high cotton production.

According to the above cases, the concept "yield" could be considered to take two possible values, either "low" when its estimated output value of yield is less than the value of 0.85 and "high" when the respected estimated output value is greater than 0.85.

The FCM tool was evaluated for 360 cases using the data of 2001 in order to calculate the average accuracy of the yield production. For these experiments, two categories of "low" and "high" yield, respectively were considered. For decision making reasons, the

threshold value has been selected equal to 0.85 by the three experts to discriminate the two yield categories – "low" and "high".

This means that if the calculated output values of yield are lower than 0.85 then the produced yield is "low" and vice versa. The estimated value of the output concept – "yield" is essential and it categorizes the cotton yield production as "low" and "high" using a simple discrimination method presented in (Papageorgiou et al., 2006).

For year 2001, the average accuracy is 73.8% which is efficient for this problem using the soft computing technique of FCMs. For the 182 cases of low yield, 135 were characterized as "low" yield and the rest as "high" yield, and for the 178 cases of high yield, 131 were characterized as "high" yield and the others as "low" yield.

The same FCM model was used with the same threshold value for the evaluation procedure to estimate the yield output for the years 2003 and 2006. The results for the three years of 2001, 2003 and 2006, are gathered in Table 4.

The yield prediction process in Precision Agriculture is depicted on the proposed flowchart which describes the procedure for taking the decision that actually determines the cotton production according to the available knowledge/data (see Fig. 11).

Implementing the NHL algorithm the FCM tool increases its ability to handle the available knowledge and to reach an acceptable decision. The FCM simulates using Eq. (3) and the weights were updated in every step till the convergence region.

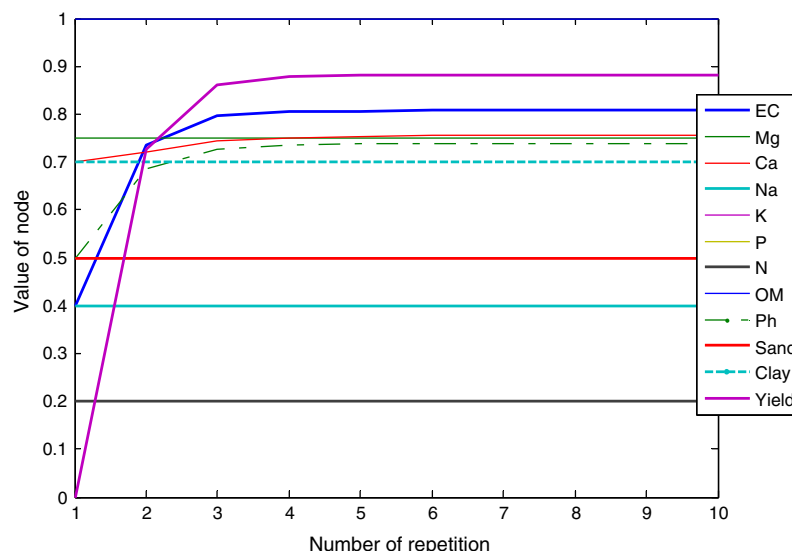


Fig. 10. Subsequent values of concepts for third case till convergence.

Table 4

Average accuracy for three years (2001, 2003 and 2006).

Accuracy/year	2001 (%)	2003 (%)	2006 (%)
Low yield	(135/182):74.18	(126/185):67.57	(103/174):59.20
High yield	(131/178):73.60	(117/175):66.86	(149/186):80.10
Average accuracy	73.80	67.20	69.65

Table 5 gathers the accuracies implementing the NHL algorithm for “low” and “high” yield categories for the three respective years of 2001, 2003 and 2006. The proposed FCM model has achieved a success of 75.55%, 68.86% and 71.32%, respectively for the years referred, in estimating/predicting the yield class between the two possible categories.

Training FCM with the NHL algorithm enhance the FCM model and incorporate the expert’s knowledge into a proper FCM model of the process or system. It seems from the results that the FCM model for cotton yield management constructed by the experts’ knowledge and enhanced by the NHL training technique works efficiently succeeding acceptable decisions for the users. Besides, this tool keeps transparency of the model and interpretability of the results. In our opinion using this fuzzy rule-based management process for cotton yield in the education process, provides a more useful environment for the practitioners than huge, hard-covered materials. It is less time consuming and easy for use for no specialists.

FCM, unlike data driven models, is built on human expertise. Moreover, its robustness does not depend on any training procedure which is biased to the size of the available data sets and feature space dimensionality. However, we agree that the selection of FCM concepts (number and type of variables used in decision making), is a very important issue in model’s design. Contrarily to current computerized support decision approaches which construct their diagnostic model only from available data, FCMs try to represent and model, the human knowledge and expertise in decision making.

Table 5

Average accuracy for three years implementing NHL algorithm (2001, 2003 and 2006).

Accuracy/year	2001 (%)	2003 (%)	2006 (%)
Low yield	(138/182):75.82	(129/185):69.73	(106/174):60.91
High yield	(134/178):75.28	(119/175):68.00	(152/186):81.72
Average accuracy	75.55	68.86	71.32

Through the literature, more studies have used statistical analysis techniques and only a few have used computational intelligent algorithms to classify and predict cotton yield from large datasets (Canteri et al., 2002; Liu et al., 2001; Miao et al., 2006). Due to the different data set it is not straightforward and possible to compare our results with those from different case studies and techniques. We only compare the results of the FCM tool with and without the unsupervised learning algorithm of NHL. The proposed FCM simulation model can be enhanced by the NHL algorithm and it simulates efficiently to estimate yield with reasonably high overall accuracy, sufficient for this specific application area.

The advantages of FCMs derive from their ability to elicit and compare the perceptions of different stakeholder experts, and to unify their viewpoints and understanding of a complex system; in this case, precision agriculture. The method can be used to integrate perspectives of both lay and expert participants; mobilizing scientific and non-scientific knowledge, values and preferences to evolve a complex and unstructured problem into a range of identifiable, albeit artificial consensus solutions. A significant advantage is that FCM does not require the direct interaction of the individuals or parties involved.

There are some general limitations of the FCM model i.e. it relates to the absence of any underlying theoretical structure for scoring preferences and explicitly conveying the heuristic values, motives and perspectives of experts. This subjectivity increases where the participants are unfamiliar with the method and the FCMs are not accompanied with additional information. Thus, our recent studies are directed towards this direction to accompany the construction methodology of FCMs with additional information from data in the form of “IF–THEN” rules by extracting the available knowledge using data mining algorithms (Papageorgiou and Groumpos, 2007; Witten & Frank, 1999).

6. Conclusion

A new modeling and simulation approach based on the soft computing technique of FCMs was introduced to address the issue of crop yield prediction. The new modeling methodology using the FCM tool was applied for the complex process of site specific management. This soft computing technique is an advanced knowledge representation and processing method that can handle the main characteristics and site specific management behavior of the cotton crop yield providing an interpretable and transparent model.

It was demonstrated that FCMs can be a useful tool for capturing the stakeholders’ understanding of the system and their perceptions on the cotton yield requirements of the precision agriculture. The main advantage of the proposed FCM decision making tool in precision agriculture is the sufficient simplicity and interpretability for farmers in decision process, which make it a convenient consulting tool in determining cotton production. With the interpretation of obtained results according to actual states, a more accurate and quick decision can be made.

This work was not intended to generate novel descriptions and predictions of cotton production but rather to create a simulation tool to help soil scientists to select soil parameters for the desired cotton production.

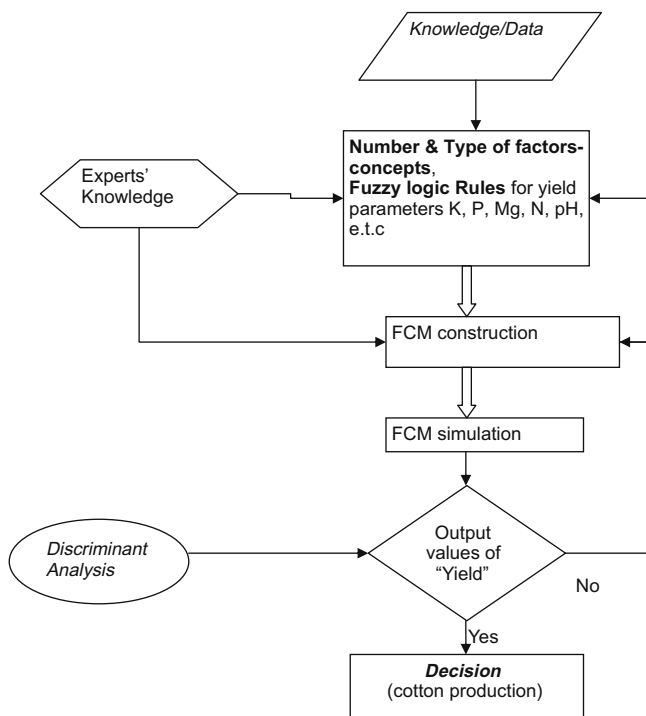


Fig. 11. Flowchart of the cotton yield trend estimation process in precision agriculture.

Our future work will be directed towards the insertion of new factors and weather conditions into the FCM model and the extension of the FCM model to work with different soil properties (for example alkaline soils). These could lead to an integrated decision support system which enhance its operation and efficiency and estimate the yield production of every field.

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