

# A PREDICTIVE ANALYTICAL APPROACH TOWARDS IMPROVING THE CROP GROWTH YIELD USING FUZZY COGNITIVE MAPS - CROYAN

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## ABSTRACT

Improving the crop yield is always a major challenge for farming community as well for agricultural scientists. Though various computational approaches have been followed traditionally in practice, still a persistent decision making method to improve crop yield is not predicted and lies as a misnomer. Multiple rethegorical factors / parameters form the basis of improved crop yield. This paper proposes Fuzzy Cognitive Map approach to help in decisive making and suggesting an optimized solution of improving crop yield as well as compared with existing approaches such as Genetic Algorithm (GA) and Artificial Neural Network (ANN). The research work considers two major crops namely Sugarcane and Red Chilli for analysis. The results show that FCM provides a higher accuracy in supporting crop growth yield with higher similarity ratio of expected growth and actual growth.

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### KEY WORDS

CROYAN, Fuzzy Cognitive Map, Crop Growth, Crop Yield, Yield Accuracy

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## INTRODUCTION

Wireless Consistent monitor and control over crop growth [11] is the major variant of precision agriculture with support of greenhouses [22], which are considered as biophysical systems with inputs, outputs and control process mechanisms which adds to cost and complexity in maintenance. Hence designing a natural crop growth and yield system with support over understanding the growth variables and formulating the decision making is the primary objective of this work.

Decision making on improved crop yield helps to:

- [a] Understand and identify the supportive metrics related to improving crop growth and yield.
- [b] Support with deterministic decision making with consistent monitoring and control over crop yield at each growth phase
- [c] Support crop growth by understanding and analyzing the environmental and demographic control parameters to estimate crop yield.

Understanding crop yield management [13] and its behavior in agricultural domain carries much importance since it relationally influences climate, region aspects or farming demographic factors. Computational approaches can be considered which support in predictive analysis of crop growth and yield. Approaches such as genetic algorithms [4][6], Artificial Neural Networks (ANN) [7], Bayesian Approach [12], fuzzy models [20] are well applicable, though such models can be adopted in complex situations, it does not achieve an optimal solution for highly dynamic and multi-variable solutions. Hence the need for an efficient knowledge-based system approach utilizing the Fuzzy Cognitive Maps (FCMs) [8] [10] approach for characterizing crop yield of behavior is discussed in this paper.

FCM is a modeling 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 for its accuracy and efficiency from the literature survey as well flexible to handle experts' knowledge and through the appropriate learning algorithms can update the initial knowledge.

Two major crops are being considered for analysis such as Sugarcane (botanical name : *Saccharum Officinarum*), Chilli (botanical name : *Capsicum annum L.*; *Capsicum frutescense L.*). These crops are considered for analysis and survey since all the three crops are well grown in India and commonly in most of the tropical regions.

The FCM model developed consists of nodes linked by directed edges, where the nodes represent the main factors in crop growth production such as soil texture, water composition as well organic matter of soil such as pH, K, P, Mg, N, Ca, Na. The directed edges show the cause-effect (weighted) relationships between the soil properties and crop grown field. The proposed method was evaluated for 300 cases measured for subsequent years such as 2007, 2008, 2009, 2010, and 2011 based upon data obtained from International Council of Agricultural Research (ICAR) and related agricultural datasets.

The proposed FCM model enhanced by the unsupervised nonlinear Bee Hive learning algorithm [23], can support a success rate on an average of greater than 75%, for years 2009, 2010 and 2011 dataset referred as estimating/predicting the yield between fuzzy categories ("worst", "low", "average", "high", "best"). 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 crop yield behavior for Chilli and Sugarcane crops. The work describes crop yield analysis being obtained from an uncontrolled farm field and not from a precision or data not obtained from temperature and hygrometric conditions in greenhouses. Hence this work carries much importance in an uncontrolled, stochastic farm field procedure.

CROYAN method works on an association based mining algorithm which is binded to the moderated patterns obtained from FCM. Fuzzy Cognitive approach observes the variable metrics and factors contributing the improved yield of crop while predictive pattern mining model determines the accuracy of selecting the crop based on variable metrics. The paper is organized as follows, Section-2 focuses on detailed survey and analysis on mechanisms to improve crop yield and need for such methods, while Section-3 elaborates on FCM and its methods, dataset and algorithm. Section-4 discusses on CROYAN with its implementation and Section-5 summarizes the work with future works to be carried out.

## SURVEY AND ANALYSIS

This section presents a detailed survey and analysis of existing works which support decisive making approaches [10, 15] for crop yield are discussed. Applying soft computational and statistical approaches for crop yield analysis is not much considered under major research challenges [20]. 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 [4], 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. Though this paper supports on decisive making and mechanisms to achieve crop yield [1,4], the detailed and in-depth analysis of the factors attributing to destruction of crop growth [2] is primarily not within the scope of this work.

Asefa Taa et al [2] discussed multiple factors which attribute to consistent crop growth needs to be automated which impose high accuracy and complexity [2]. The phenomenon of crop growth cannot be completed automated or sensed upon due to the need for supporting precise and periodical evaluation of biotic status of crops and their natural growth. This paper discusses on the underlying factors behind design and implementation of a crop yield decision making system which adopts growth and yield sensitive metrics on control and monitoring growth process of crops. This approach is compared and analyzed over similar crop growth trends which are achieved over similar climatic and regional factors phenomena.

## NEED FOR FUZZY COGNITIVE MAPS

As artificial intelligence and heuristic approaches are not often sufficient to obtain high quality prediction, the proposal can be extended to supplement using knowledge base and adaptive soft computational approaches. Predicting crop yields at an early stage in the growing season can be of great importance. The correlation of the corn yield [7, 16] helped to permit the early yield prediction and the appropriate management of the farm land.

Crop growth models were developed in agriculture by using mean values of input and outputs [17]. Several crop growth models have been developed by Xirogiannis [19]. Papageorgiou [13] presents the soft computing technique of Fuzzy Cognitive Maps (FCM) to connect yield defining parameters with yield in cotton crop production in India as the basis for a decision support system for precision agriculture application. FCM was chosen because of the nature of the application as it is a complex process and FCMs have been proved suitable for this kind of problem. Due to consistent change in temperature and hygrometric conditions, rapid decisions are highly essential to predict and control yield of crop or manage diseases to avoid dissemination and permanent infestation of crop growth [4] [12] hence soft computational approaches would suffice.

## METHODS

The methods and procedures being followed can be summarized.

### (a) Data Set

The dataset collected over 300 record sets consisting of weather, soil, water, regional and crop growth data over the year 2007, 2009, 2010, 2011 catering to the region of Dharwad in Karnataka and Cuddalore in Tamilnadu for Sugarcane crop and Guntur in Andhra Pradesh and Madurai in Tamilnadu for Redchilli crop. The results are compared with bench marking genetic algorithm and ANN systems

### (b) Metrics adopted

Few of the major metrics adopted in this research work are (i) Average yield achieved over per year (tons/ha), (ii) Average crop production per year each ha, (iii) Mean Crop Yield

### (c) Soil - Water

Total Soil-Water Potential (SWP) can be used to determine the capacity of water available for crop transpiration from each soil layer. The capacity of the soil to hold enough water supports the growth of crop. Hence type of soil and water has a potential role in crop growth as well yield

### (d) Role of NDVI

NDVI (Normalized Difference Vegetation Index) along with variable crop growth metrics suggests a useful way for crop yield assessment models whose approaches vary from simple integration to more complicated transformation. NDVI [9] has proved to improve vegetation greenness, which indicates the level of healthiness in the crop growth

### (e) Selection of crop and growth region

Major Chilli growing states in India are Andhra Pradesh, Tamil Nadu, Maharashtra, and Karnataka which together constitute nearly 75 per cent of the total area. Hence dataset has been collected for Guntur (16.3008° N, 80.4428° E), and near by regions such as Khamman and Cuddappa in State of Andhra Pradesh. In Tamilnadu, Sugarcane dataset in Karur district (10.9338334 N, 78.0883645E) and near by Erode are collected for analysis. In both the regions Chilli variety K-1 and CO-1 are used for analysis while CO-265 variety for Sugarcane crop.

## FUZZY COGNITIVE MAP

Fuzzy cognitive maps (FCM) [3] [8] along with SVM (Support Vector machines) [5] helps in understanding and modeling crop yield and representing crop expert knowledge, since fuzzy cognitive theory [6] supports on theory of fuzzy logic and cognitive map, which are capable of dealing with uncertainty issues.

### Modeling approach using Fuzzy Cognitive Maps

Fuzzy Cognitive Map (FCM) methodology [14, 17] is a symbolic representation for the description and modeling of complex system. Fuzzy Cognitive Maps describe different aspects in the behavior of a complex system in terms of concepts. FCMs illustrate the whole system by a graph showing the cause and effect along concepts, and are a simple way to describe the system's model and behavior in a symbolic manner, exploiting the accumulated knowledge of the system. A Fuzzy Cognitive Map integrates the accumulated experience and knowledge on the operation of the system.

Fuzzy Cognitive Maps (FCM), Tsadiras [18], defines it as a qualitative alternative approach to formulate dynamic systems. This approach can be considered to represent formal method to represent predictions and taking decisions. This work investigates the crop yield and variability crop yield prediction in chilli and sugarcane crops.

Crop management in these crops are highly complex with interacting parameters such as water, climate, soil factors which play major role in improving the yield of crop.

The FCM model possess nodes which show the variable factors affecting crop yield using a directed graph G(V,E). The cause effect relationship between the factors and crop yield can be depicted and analyzed. As shown in Fig-1 each components or elements contributing to growth of crop can be considered as Node, 'Na', through 'Ne' while all linkages which may be related between multiple nodes can be termed as Edges as 'E1' through 'E6', generally as Ei.

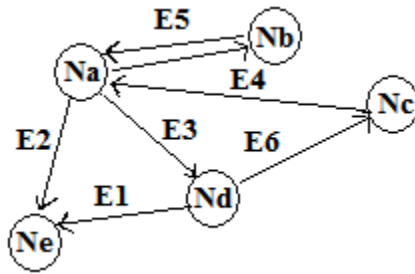


Fig:1. FCM representation using graph theory G (V,E)

FCM assigns a weight as 'Ei' for each edge, and each node 'Ni' binds the value to its weight. The causal relationship between two concepts Nj and Ni in fuzzy is explained with weights Ei, which considers the value in the range -1 to 1. Three possible types of causal relationships between concepts are followed:

- (a)  $E_i > 0$  which indicates positive causality between concepts Nj and Ni, which indicates that an increase or decrease in the value of Nj leads to an increase (decrease) in the value of Ni.
- (b)  $E_i < 0$  which indicates negative causality between concepts Nj and Ni, which indicates that an increase (decrease) in the value of Nj leads to a decrease (increase) in the value of Ni.
- (c)  $E_i = 0$  which indicates no relationship between Nj and Ni.

The FCM process can be inferred from the following mathematical formulation in equation 1.

$$g_i^{k+1} = f \left( g_i^{(k)} + \sum_{j=1}^N g_j^{(k)} \cdot E_i \right) \longrightarrow 1$$

Here, gi denotes the value of Ni node, while simulation is carried out over 'k', Ei is the linkage value between two nodes 'Ni' and 'f' is a sigmoid threshold function, which is  $1 / (1 + e^{-x})$ .  $\square$  lies between a value [0,1]. The fuzzy metric for crop yield lies between the ranges {low influence, moderate influence, acceptable influence, strong influence, best influence} over crop growth and production.

The fuzzy IF-THEN rules that experts use to describe the relationship among concepts assume the following form, where A and Bare linguistic variables:

IF value of concept INFLUENCE Ni is "Low", AND  
value of concept INFLUENCE Nj is "Average" THEN linguistic weight INFLUENCE Ei is "Acceptable"

where Low, Average, Acceptable are linguistic INFLUENCE variables taking values in the range [0, 1].

Each interconnection described by a fuzzy linguistic variable from the determined set, associates the relationship between the two concepts and establishes the grade of causality between the two concepts.

### Mapping the component values between the edges and variable nodes

The dataset collected over 300 cases consists of weather, soil, water and crop data during the years 2007, 2008, 2009, 2010 and 2011 for the region of Guntur in Andhra Pradesh. The Sugarcane data obtained for 250 record sets are obtained from Karur in Tamilnadu. The data is validated with base line data and maintained as repository. The results are compared with bench marking fuzzy and Artificial Neural Networks (ANN) systems.

## RESULTS AND DISCUSSION

### CROYAN: Crop yield analysis using FCM approach

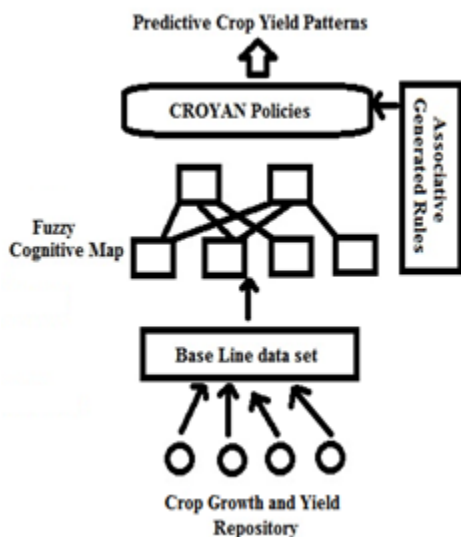


Fig. 2. CROYAN architecture and functionality

Figure-2 explains CROYAN architecture which extracts the features of crop growth from data set and determines the crop yield efficiently. The baseline dataset is validated based on historical datasets and verified. FCM is being generated on crop growth parameters using metrics [Table-1]. Polygon clusters are generated for variable growth parameters.

The coefficients of empirical equation have been obtained using a analytical breakpoint (m) based on optimization of a mean of three years of Sugarcane and Chilli crop yield. [Table -2] shows the breakpoint achieved when the actual maximum yield achieved is equivalent to the expected yield. CROYAN methodology uses polygonal analysis to mine related datasets, which formulates the following steps:

1. Collect/Generate polygonal clusters for multiple related datasets
2. Meta cluster polygonal clusters
3. Extract interesting patterns / create summaries from polygonal clusters

CROYAN methodology adopts a multi clustered polygon based architecture, which defines variable multiple clusters required to identify the fitness of crop yield. Polygonal clusters [14] defined using Hausdroff metric suggests each clusters based on crop type, region associated with crop growth and production as shown in Figure-3. Each polygonal clusters originating from different datasets typically overlap, which provide an option to restrict cluster overlap in final clustering. Each clusters usually assumes that inter dependent polygons do not overlap and most uses the Hausdroff distance [11] to assess polygon similarity for crop yield. Figure-3 shows the set of polygonal clusters which depends on crop sow values and its relational yield values. This measure is vital in its definition due to its need for identifying the crop growth measure which is required for identifying the crop yield.



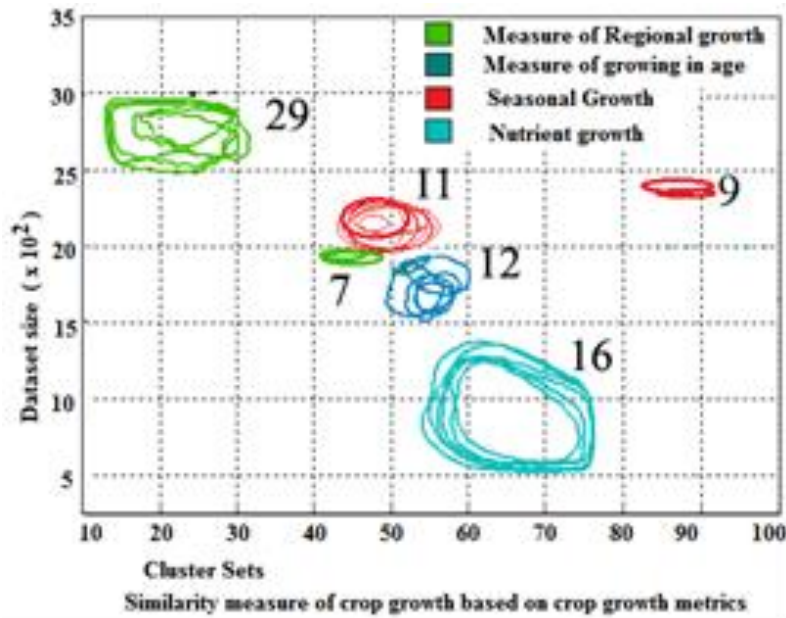


Fig. 3. Cluster sets generated as polygonal clusters

### CROYAN inputs and definition

A clustering set  $S = \{X_1, \dots, X_n\}$  — at most one metric is selected from each meta cluster  $X_i$ , ( $i=1, \dots, n$ ).

1. The crop growth provides individual cluster crop yield function  $FitU$  whose values are  $[0, \infty)$ .
2. A fitness threshold value defined with  $\theta U$   
 $U$  being set of lower unfit clusters are occupy not included in the final clustering.
3. A cluster distance threshold  $\theta_{croyan\_dist}$  which determines the cluster overlap/coverage can be tolerated.
4. A cluster distance function  $Z$  is defined between clusters of  $croyan\_dist$ ,

For  $X_i \subset S$ , where  $i = 1 \dots n$

Begin

Find  $Z \subseteq X_1 \cup \dots \cup X_n$  that maximizes:  $q(Z) > FitU(X_i)$

subject to:

- a)  $\forall X \in Z \forall X' \in Z (X \neq X' \Rightarrow croyan\_dist(X, X') > \theta_{croyan\_dist})$
- b)  $\forall X \in Z (FitU(X) > \theta U)$
- c)  $\forall X \in Z \forall X' \in Z ((X' \in X_i \in S \wedge X \neq X') \Rightarrow i \neq n)$

End

The goal is to maximize the number of fitness measures of crop yield among clusters which have been selected from polygon clusters. The constraint 'a' prevents any two clusters that are too close to each other but are both included in the final clustering. Constraint 'c' makes sure that at most one cluster from each cluster being selected. Constraint 'b' determines the policy for fitness measure where the fitness can satisfy step (2). Here,  $Z$  is the cluster distance function defined based on CROYAN distance threshold level,  $FitU$  is the fitness measure obtained to understand the optimal crop yield.

### Model

The FCM model possess nodes which show the variable factors affecting crop yield using a directed graph  $G(V, E)$  shown in **Figure-1**. The cause effect relationship between the factors controlling the crop yield and aspects which support in crop yield can be analyzed.

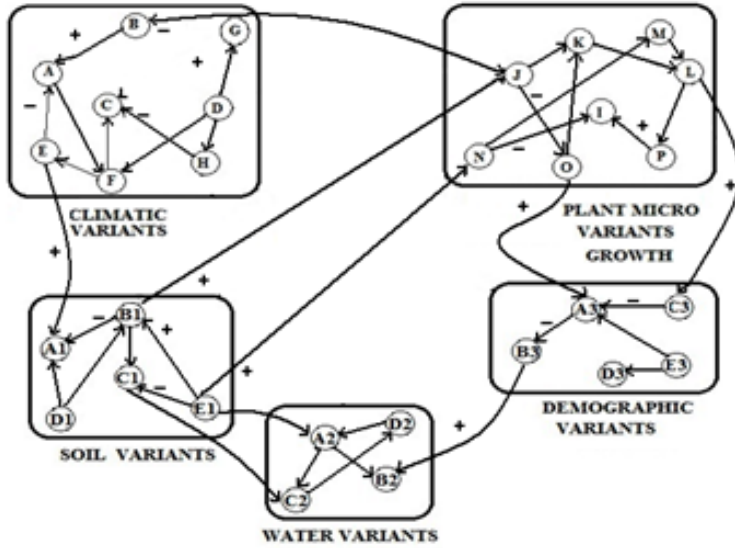


Fig: 4. Crop Yield analysis based on FCM variant metrics

Figure-4 shows the analysis of metrics required for crop growth, over variable FCM nodal components such as climatic variants, growth micro-variants, regional demographic variants, water and soil variants. Each variant possess multiple crop growth dependent elements which plays a vital role in crop production and detecting the yield.

### Analysis and predictions

Early detection of crop yield growth symptoms or initial analysis of NDVI parameters related to the key-point in the crop yield index (CYI) Support in gathering the climatic data through meteorological stations, data on crop growth rendered by agricultural stations were the primary means of data collection procedure. This work adopts the following crop growth metrics such as temperature condition index (TCI) for mapping and monitoring of crop growth metric which also indicates the assessment of vegetation health and productivity. Variable parameters such as TCI, soil moisture, surface temperature and average rainfall as shown in Fig-5 are the valuable sources of information for the estimation and prediction of crop growth conditions.

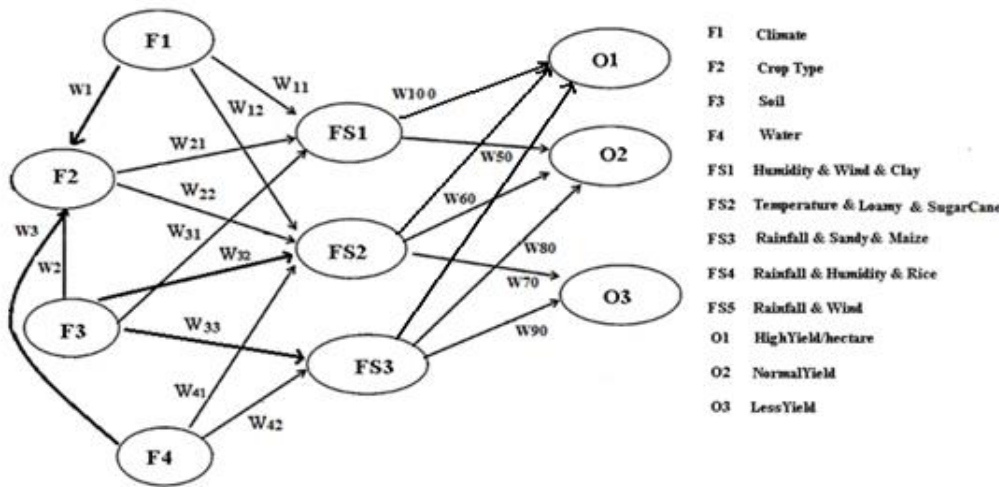


Fig: 5. FCM mapping of Chilli crop growth parameters and its corresponding outcome 'O'

Figure-5 shows components ‘Fi’ as metrics responsible for Chilli crop growth, which are interdependent on one other and hence map to ‘FSi’ components as primary variables that plays vital role in crop growth. ‘Oi’ depicts the final outcome of crop growth outcome, which may be “High in Yield” or “Normal Yield” or “Less Yield”. Similar sugarcane crop growth can be obtained using FCM approach. ‘Wi’ indicates the weight assigned for components on priority, which gets updated based on crop yield based metrics. For any change in weight, the component required for yield also gets varied.

The actual crop yield achieved over Chilli and Sugarcane compared with higher predicted yield for crops were compared as shown in [Table-2]. The Residual crop yield becomes equal to expected change in crop yield, based on condition of growth issues which primarily depends on breakpoint applied. The model empirical equation for Sugarcane and Chilli crops, thus obtained with coefficients [Table- 2] is given as:

Table: 1. FCM nodal components adopted for CROYAN

A	Precipitation Value/ day
B	Maximum Cloud Cover/ day
C	Radiation Sunshine/ day
D	Vapour Pressure/ day
E	Wind Pressure/ day
F	Snow Depth/ day
G	Average Humidity/ day
H	Average Temperature/ day
I	Monthly Average Rainfall
J	Soil Ph concentration
K	Soil nutrient value
L	Water Ph value
M	Air Pollution Level
N	Climatic Metrics
O	Nutrient Manure metric
P	Water nutrient metric
A1	Soil Type
B1	Soil composition
C1	Soil Manure
D1	Percentage of Anti-oxidants
E1	Soil Humidity
A2	Water type
B2	Water Composition
C2	Oxidation Ratio
D2	Water mineral and pollutant ratio
A3	Soil Plough methods
B3	Crop watering interval
C3	Weed removal methods
D3	Manure laying methods
E3	Pesticides application methods

Table: 2. Achieving crop yield using FCM. Predicted and observed crop yield of Sugarcane for Karur, Tamilnadu and Chilli crop for Guntur, Andhra Pradesh using Fuzzy Cognitive Maps

Year	Sugar cane crop yield			Chilli crop yield		
	Predicted	Actual / Observed	Residual	Predicted	Actual /Observed	Residual
2007-J	120.8	119.5419	1.2581	36.5	34.9126	1.5874
2007-A	87.112	83.7547	3.3573	32.0	31.2125	1.7875
2008-J	126.13	120.6428	5.4872	31.5	32.8647	-1.3647
2008-A	139.130	138.4765	0.6535	38.0	36.8840	1.1160
2009-J	134.118	133.1821	0.9359	41.5	41.9016	-0.4016
2009-A	126.117	125.7217	1.3953	43.5	43.3660	0.1340
2010-J	99.462	98.5832	0.8788	35.0	34.2990	1.2990
2010-A	124.138	123.8340	0.3040	39.0	37.7836	1.2164
2011-J	138.145	137.5609	0.5841	41.9	41.5585	0.4585



The SSToolbox 3.61 [21] software supports methodology to store, represent, filter and analyze the acquired field data. All the collected data were interpolated in order to produce a map on a 10m x 10m grid size that corresponds to a reliable field management unit. The years are indicated in two formats as 'J' for January yield, 'M' for may yield, 'A' for august yield and 'O' for October yield. It can be observed from [Table-2] that the residual crop yield is 87.42% predicted similar both for sugarcane and Chilli crop.

### Performance analysis

The performance of CROYAN is analyzed over crops Chilli and Sugarcane which are well grown in humid temperature climatic regions. Crop growth parameters required for crop growth, to improve the yield and improve production, are considered for analysis.

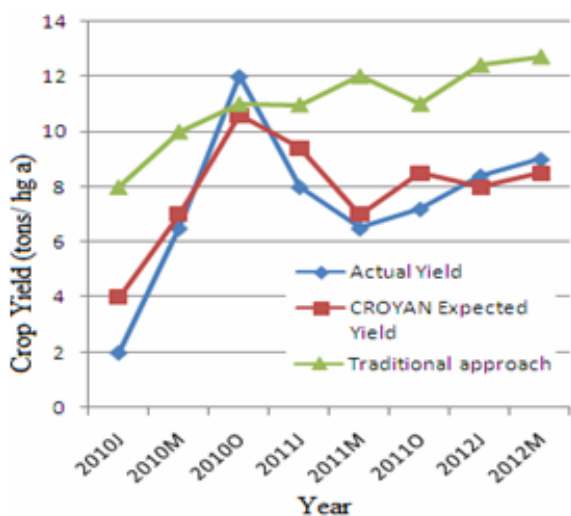


Fig: 6 Sugarcane Crop yield obtained for actual yield, expected yield using CROYAN

Figure-6 discusses on Sugarcane crop yield achieved using CROYAN analytical approach during the years 2010 to 2012 for the months Jan, May and October respectively. It is understood that the yield analysis using actual and expected is averaging over 5.93% to 7.27%. The accuracy of actual yield over the predicted yield confirms the performance of CROYAN for Sugarcane crop.

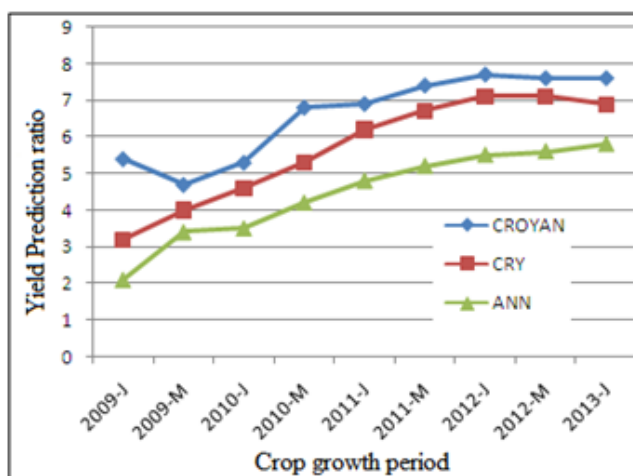
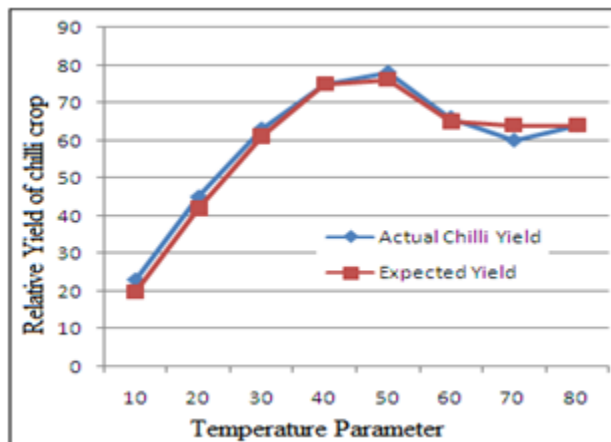


Fig: 7. Crop Yield analyzed over CROYAN and other approaches

**Figure-7** compares the performance of crop yield analysis over CROYAN, CRY approach which uses Bee Hive computational approach and ANN approach which shows that the yield prediction ratio achieved over CROYAN is higher than other approaches. ANN approach show a lower performance for the dataset used with 250 records primarily due to memory occupation during runtime and achieve local optima.



**Fig: 8 Chilli Crop Yield achieved for Actual and Observed Yield**

**Figure-8** explains the performance of CROYAN over Chilli crop, where the observed yield and predicted yield are analyzed for variable 'H' [Table-1] for temperature as metric. The obtained yield is identified to be relative to temperature which aids in growth of Chilli crop for Guntur region. As Chilli crop is highly grown under humid climates as well in regions which require high sunlight, the field 'H' is considered for analysis.

## CONCLUSION

This work investigates the crop yield and variability crop yield prediction in Chilli, Sugarcane. Fuzzy Cognitive Map is adopted in this research work to suggest and identify the yield among crops. The analysis had been carried out using NDVI parameters and its CYI metrics which determine the yield estimate and reference metrics. FCM approach is compared with other traditional approaches, such as CRY and ANN approaches, it can be noticed that CROYAN approach converges to every local optimum, hence the observed yield and actual yield datasets has much similarities. Further the work can be improved to find the suitability of variable climatic situations and challengeable crop growth analysis.

## CONFLICT OF INTEREST

Authors declare no conflict of interest.

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None.

## FINANCIAL DISCLOSURE

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