Implementation of Fuzzy Logic in Estimating Yield of a Vegetable Crop

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Abstract. Predicting the influence of climate variations on crop yield demands an appropriate model. In this study, Fuzzy logic based crop yield estimation is undertaken considering temperature, humidity and moisture of soil as input parameters. By subjecting these parameters to fuzzy arithmetic, crisp value of yield is obtained. Trapezoidal membership function is considered in the fuzzy modeling. The results are validated using available open source literature. It has been verified theoretically that air humidity 65%-75%, air temperature 18-290 C and soil moisture 60-80% would give high yield.

1. Introduction

Forecasting the crop yield would assist the strategies of farmers, industries and government. The potential growth and yield is dependent on several production attributes such as soil properties, weather, fertilizer, topography and irrigation management. Largest consumers of freshwater in the world is food and agriculture sector which accounts to one hundred times more than used for personal needs. Irrigation requires 70% of the water, 20% industry and 10% domestic applications. To meet the food requirement of world population (about 6 billion) water required is 6000km$^{3.}$ Most of this requirement is met through rainfall and through irrigation 15% is provided. Thus, per year 900 km^3 of water is required for food crops through irrigation. The United Nations Dept. of Economic and Social Affairs estimates global population to stretch between 8.4-8.6 billion by 2030. In future global water demand for agriculture is assessed to increase further 19% (See [1], [2] & Figure1.& Figure 2.). Thus, in future competition for water resources is anticipated. Significant water saving support system is anticipated to support continued economic growth.

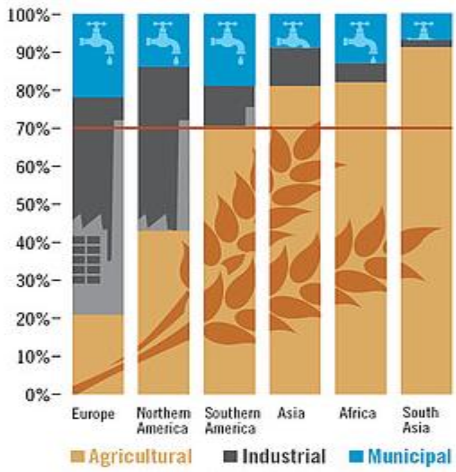

Figure 1. Share of freshwater withdrawals by sector

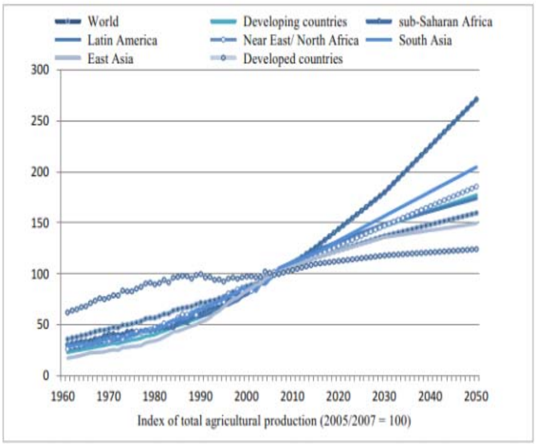

Figure 2. Agricultural Production by region

Fuzzy logic theory is extension of Boolean logic and it expedites logical values between true/false. In 1963 Fuzzy logic theory was introduced and was implemented in Japan during 1998. Fuzzy logic theory facilitates the combination of multiple values of single parameters / multiple parameters together to construct a rational result. Thus, very helpful to operate and find accurate solution to the ambiguity of the real word problem in all the sectors such as artificial intelligence, biomedical, agriculture, environment, industrial control etc. Recently, Peng and Liu [3] designed water- saving irrigation model adopting wireless sensor network along with fuzzy control method considering soil and humidity information. Anand et al. [4] demonstrated automatic drip irrigation model with mobile technology and fuzzy logic considering input parameters such as soil humidity, air humidity, temperature and salinity. Bahat et al. [5] modeled fuzzy irrigation controller system considering input variables wind speed, temperature, air humidity, water budget. Paucar et al. [6] designed decision support by wireless distributed sensors for smart irrigation. Umair et al. [7] modeled ANN based controller for automation of irrigation system. Dela Cruz et al. [8] adapted Neural Network to optimize water usage in automated irrigation system. Jimenez et al. [9] by using devices raspberrypi and xbee, looking at the factors soil moisture, temperature, luminosity and rain data developed irrigation scheduling system. Karimah et al.[10] designed smart pot implantation considering internet of things. Related work regarding the water saving, smart irrigation management and estimation of yield by the implementation of various current technologies can be found in [11-25].

After tomatoes and peppers it is the green beans which is the third most popular vegetable grown in the home gardens this vegetable is belongs to leguminocae family. It is cultivated for about more than 7000 years worldwide. Loamy soil is ideal to grow green beans. Europe and Asia are the dominant producers of green beans with more than 30% and 50% of world production. Green beans is one of the most important vegetable it provides vitamins, protein, calories and minerals (calcium, iron and phosphorus).

2. Problem Definition

In this paper estimation of crop yield is undertaken using fuzzy inference system. Crop analyzed in this study is green beans.

Three fuzzy input variables or factors have been considered, viz.,

a. Humidity
b. Temperature
c. Moisture of Soil

Figure 3. shows the basic approach to the problem. The fuzzy inference system takes linguistic inputs (as stated for simplification), processes the information and outputs the performance. The outputs are turned back to the real numbers using a defuzzification procedure.

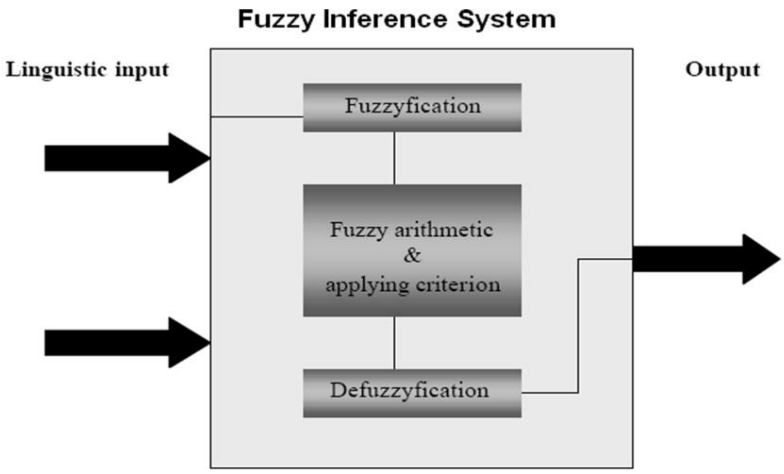

Figure 3. Fuzzy Inference System

2.1. Details about the Set Applied

Before the details of the fuzzy system are dealt with, the range of possible values for the input and output variables are determined. These (in language of Fuzzy Set theory) are the membership functions (Input variable vs. the degree of membership function) used to map the real world measurement values to the fuzzy values, so that the operations can be applied on them. Fig. 4- 7 shows the labels of input and output variables and their associated membership functions i.e., trapezoidal membership functions using Mamdani method.

Values of input variables**:** (a) Humidity: Humidity input variable has three membership functions. Dry, Normal and Moist.

The functions used to map humidity inputs in terms of % into fuzzy sets are:

$$\mu Dry\ Humid[x] = \begin{cases} 1 & 0 \le x \le 25 \\ \dfrac{50-x}{50-25} & 25 < x \le 50 \\ 0 & 50 < x \le 100 \end{cases}$$

$$\mu Normal\ Humid[x] = \begin{cases} 0 & 0 \le x \le 40 \\ \dfrac{x-40}{60-40} & 40 < x \le 60 \\ 1 & 60 < x \le 70 \\ \dfrac{80-x}{80-70} & 70 < x \le 80 \\ 0 & 80 < x \le 100 \end{cases}$$

$$\mu Moist\ Humid[x] = \begin{cases} 0 & 0 \le x \le 60 \\ \dfrac{x-80}{80-60} & 60 < x \le 80 \\ 1 & 80 < x \le 100 \end{cases}$$

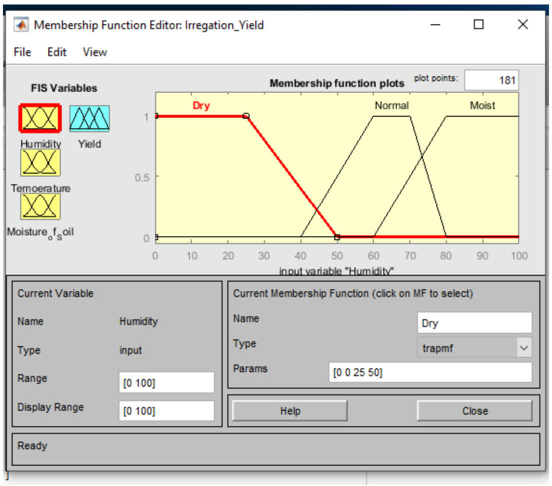

Figure 4. Humidity membership function

(b)Temperature in terms of Celsius (^{0} C) scale Low, Normal, High. The functions used to map Temperature inputs into fuzzy sets are:

$$\mu LowTemp[x] = \begin{cases} 1 & 0 \le x \le 9 \\ \dfrac{18-x}{18-9} & 9 < x \le 18 \\ 0 & 18 < x \le 50 \end{cases}$$

$$\mu Normal\,Temp[x] = \begin{cases} 0 & 0 \le x \le 9 \\ \dfrac{x-9}{18-9} & 9 < x \le 18 \\ 1 & 18 < x \le 27 \\ \dfrac{36-x}{36-27} & 27 < x \le 36 \\ 0 & 36 < x \le 50 \end{cases}$$

$$\mu HighTemp[x] = \begin{cases} 0 & 0 \le x \le 27 \\ \dfrac{x-27}{36-27} & 27 < x \le 36 \\ 1 & x \ge 36 \end{cases}$$

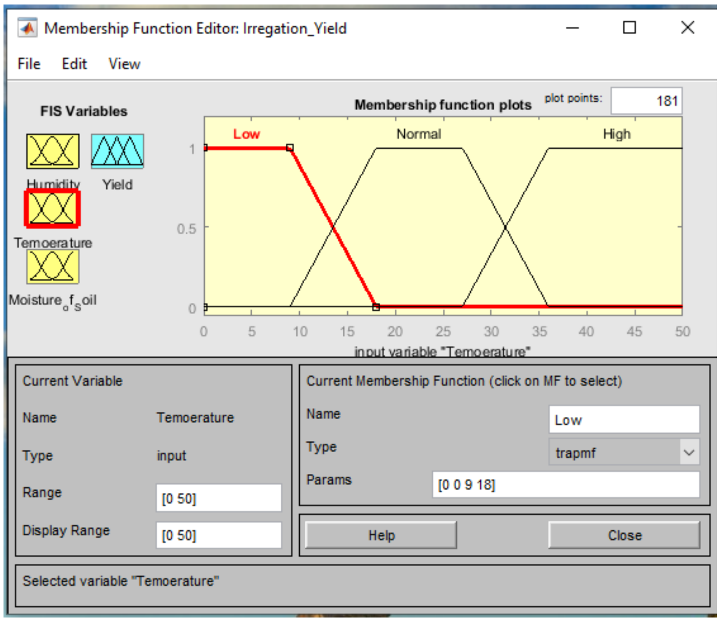

Figure 5. Temperature membership function

(c) Moisture of Soil: Moisture of Soil input variable has three membership functions: Low, Normal and High. The functions used to map Moisture of Soil inputs into fuzzy sets are:

$$\mu DryLow[x] = \begin{cases} 1 & 0 \le x \le 40 \\ \dfrac{60-x}{60-40} & 40 < x \le 60 \\ 0 & 60 < x \le 100 \end{cases}$$

$$\mu Medium\, Moist[x] = \begin{cases} 0 & 0 \le x \le 50 \\ \dfrac{x-50}{70-50} & 50 < x \le 70 \\ 1 & 70 < x \le 80 \\ \dfrac{90-x}{90-80} & 80 < x \le 90 \\ 0 & 90 < x \le 100 \end{cases}$$

$$\mu High\, Moist[x] = \begin{cases} 0 & 0 \le x \le 80 \\ \dfrac{x-80}{90-80} & 80 < x \le 90 \\ 1 & 90 < x \ge 100 \end{cases}$$

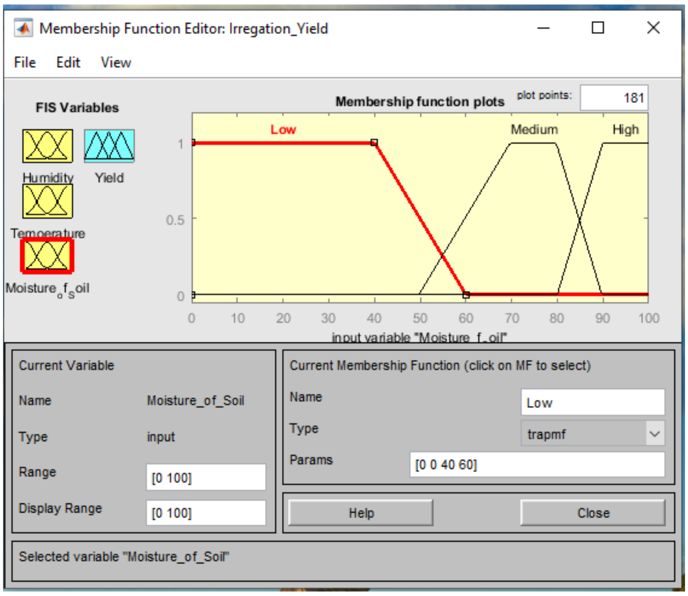

Figure 6. Moisture of Soil membership function

The value of the output variable i.e., crop yield has three membership functions: Low, Medium and High The functions used to map crop yield inputs into fuzzy sets are:

$$\mu YieldLow[x]=\begin{cases}0 & x\le 0\\ 1 & 0<x\le 20\\ \dfrac{40-x}{40-20} & 0<x\le 20\end{cases}$$

$$\mu YieldMedium[x]=\begin{cases}0 & x\le 30\\ \dfrac{x-30}{45-30} & 30<x\le 45\\ 1 & 45<x\le 55\\ \dfrac{70-x}{70-55} & 55<x\le 70\end{cases}$$

$$\mu Yield\ High[x]=\begin{cases}0 & x\le 60\\ \dfrac{x-60}{80-60} & 60<x\le 80\\ 1 & x\ge 80\end{cases}$$

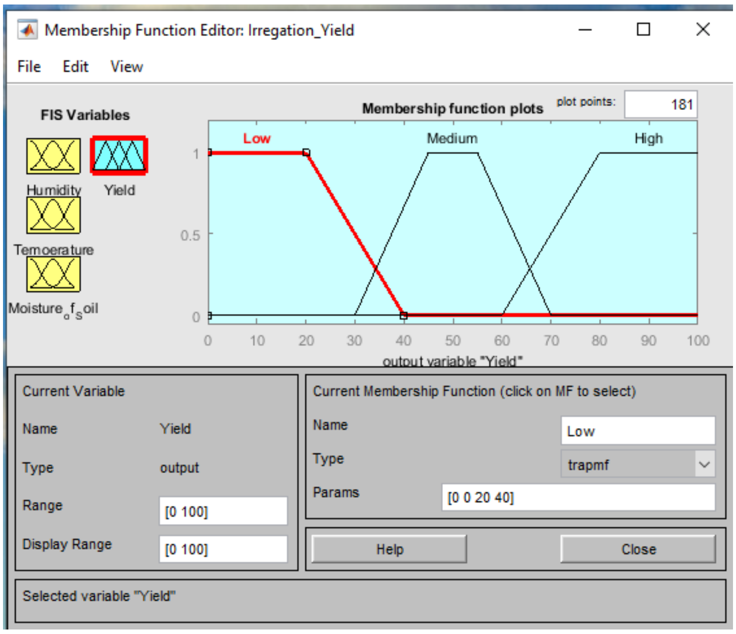

Figure 7. Output function

3. Results and discussion

By differing the scale values of all the input variables Humidity, Temperature and Moisture of Soil results are obtained according to the rules. Fig.8 portray rule editor which lets generating rules based on different combinations of input and output parameters. Fig.9 portray the rule viewer of fuzzy toolbox. Range membership functions, i.e., from 'Low' to 'High' varies from 0 to 100 via increasing the values of input variables. The estimated yield in percentage is shown in Table 1. The fuzzy toolbox of MATLAB software is used for obtaining the output value. Fig. 10 portray that when humidity is normal and soil moisture is medium yield is high. Fig. 11 shows when temperature is normal and humidity is high yield is not much. It has been verified theoretically that air humidity 65%-75%, air temperature around 18-29^0 C and soil moisture 60-80% would give high yield. The results almost coincide with the information available in the open literature (see, [26]).

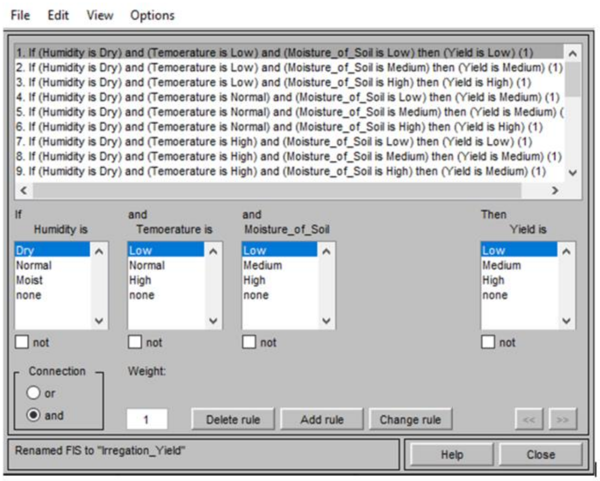

Figure 8. Rule Editor

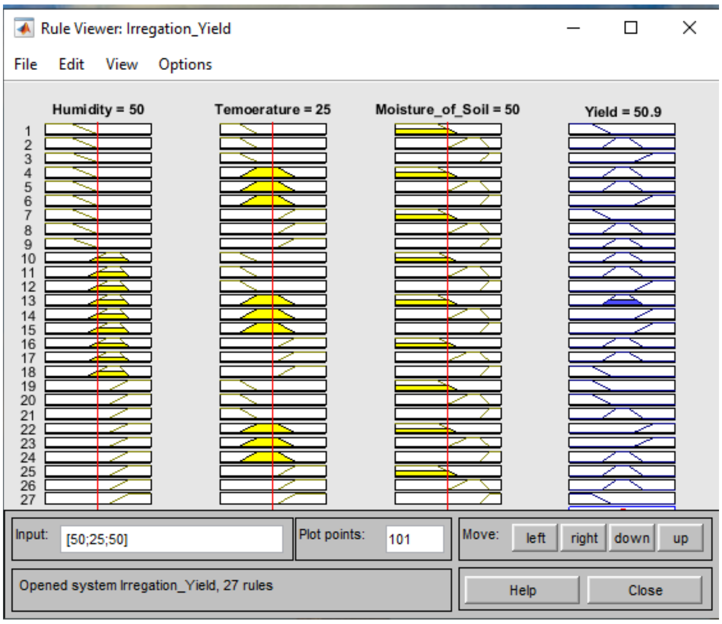

Figure 9. Rule Viewer

Table1. Yield of green beans for different input values.

Humidity(%)	Temperature (^{0}C)	Moisture of Soil(%)	Yield(%)
65	18	60	83
75	29	80	75
68	25	70	85
40	40	50	18
80	40	90	15
95	45	90	16
25	8	30	15
50	50	80	50
20	9	30	15
10	10	35	19
30	25	40	50

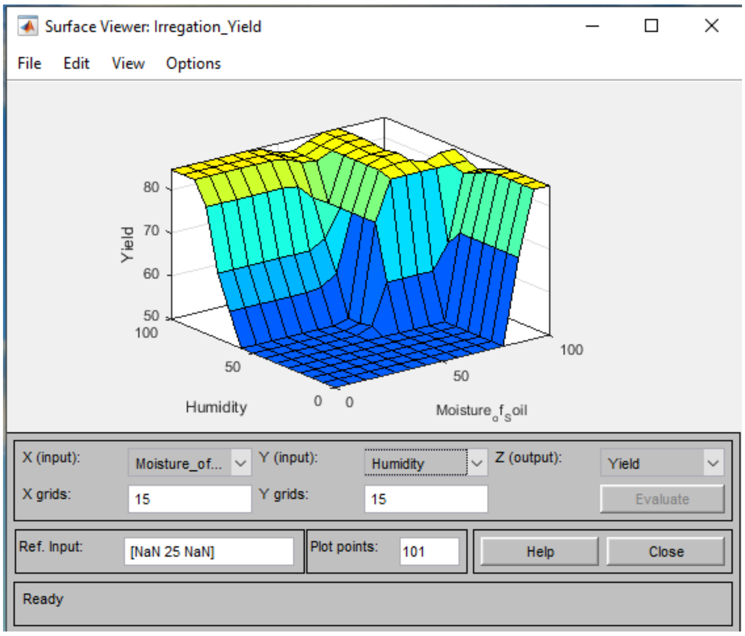

Figure 10. Humidity and Moisture vs Yield possibility

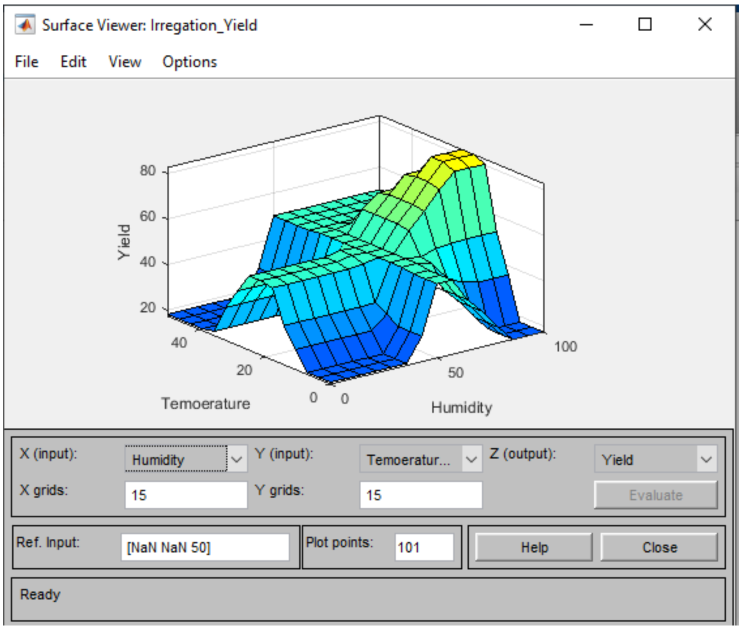

Figure 11. Temperature and Humidity vs Yield possibility

4. Conclusion

By the use of fuzzy inference system in this study, possibility of growth of green beans for different parameters is analyzed. Green beans are warm season crop which can be grown once frost has passed in spring, full sunlight. It has been verified theoretically that air humidity 65%-75%, air temperature around

18-29^0 C and soil moisture 60-80% would give high yield. The purpose of this study was only analysis not recommending any counter scheme. This study might be useful for developing latest irrigation methods and optimal yield.

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