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CROP YIELD ESTIMATION USING FUZZY LOGIC MODELLING & WEATHER PARAMETERS

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Abstract – *In current times the changes in climate are very prompt and uncertain which require pre-handling and efficient planning of farming activities. The uncertainty of the sudden climatic changes impact the crop growth and yield in an uncertain manner. Thus there is need of developing fuzzy approach based mathematical models to handle this uncertainty. Fuzzy logic, in particular, has gained prominence for its ability to accommodate ambiguity and uncertainty, offering a powerful means to predict crop yields and detect diseases at early stages, thereby facilitating prudent crop planning and management. It operates on a foundation of mathematical principles that hinge on the concept of degree of membership, diverging from conventional binary logic and excels in scenarios where vague or uncertain information prevails, an attribute that proves invaluable in the realm of agricultural diagnosis. In realm of the existing weather conditions this study is conducted based on monthly gathered data spanning over a 20-year period, from 2001-2002 to 2019-2020, encompassing nine key weather parameters. These parameters included maximum temperature, minimum temperature, saturation vapor pressure (SVP), relative humidity, wind speed, average wind speed, bright sun hours, pan evaporation, and rainfall. For the prediction of crop yields for Wheat, a multiple linear regression model was employed. This technique identifies the primary weather-related factors or predictors that influence crop yield, forming the basis for yield prediction using fuzzy logic.*
Keywords: **Fuzzy logic system, Yield estimation & prediction, Multiple linear regression, Weather parameters.**

1.INTRODUCTION

In the context of contemporary agricultural practices, the utilization of mathematical models has evolved into an indispensable instrument for comprehending and efficiently managing intricate agricultural systems. This comprehensive exploration delves into the pivotal role that mathematical models play within the agricultural domain, spanning from their basic principles to their pragmatic applications[1]. Soft computing techniques, like fuzzy logic forms a part of modelling used in agriculture crop planning. Fuzzy logic, in particular, has gained prominence for its ability to accommodate ambiguity and uncertainty, offering a powerful means to predict crop yields and detect diseases at early stages, thereby facilitating prudent crop planning and management.

Agriculture is inherently dependent on weather, which plays a critical role in the agricultural production system. Weather conditions influence the growth, development, and yield of crops, as well as the incidence of pests and diseases, water requirements, and fertilizer needs. Key factors such as temperature, rainfall, sunlight, relative humidity, wind speed, and wind direction significantly affect crop health and productivity. Weather conditions being erratic and unsure, needed to be properly dealt with & fuzzy logic indeed provides a robust framework for dealing with the uncertainties and complexities inherent in agricultural systems. Unlike binary logic, which requires clear-cut definitions, fuzzy logic accommodates the nuances and gradations that are often present in real-world scenarios. It enables farmers to make informed decisions about planting, irrigation, fertilization, and harvesting, ensuring that crops are cultivated at the optimal time. This proactive approach can minimize crop losses due to extreme weather conditions, ultimately improving agricultural efficiency and sustainability [2].

Crop yield prediction is based on a variety of data types that are gathered and extracted from several sources using data mining techniques and are helpful for crop growth. It is an art to predict crop output and quantity ahead of time, that is, before the harvest really occurs. For farmers, estimating the crop output can be quite helpful. If they are aware of the yield they may anticipate, they can reduce their crop before harvest, which frequently results in a more favourable price than they get if they wait until after

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harvest. Experts' engagement in agricultural production forecast causes problems such as weariness, denial of personal perception, and ignorance of natural phenomena. These problems can be resolved by applying the models and tools for crop production phenomenon.
Yield estimation or prediction of a crop is the need of today's time for every government for making various policy decisions relating to storage, distribution, pricing, marketing, import-export etc. In this research the focus lies on a crucial step in effective crop planning: the estimation and prediction of crop yields (kg per hectare) for Wheat, for the western zone district Hisar, of Haryana, using monthly average of weather parameters viz. maximum temperature, minimum temperature, saturation vapour pressure (SVP) SVP M, SVP E, Relative humidity M, Relative Humidity E, Wind speed M, Wind speed E, average speed, bright sun shine, pan evaporation, rainfall. The technique of regression analysis is applied on twenty years of weather data 2001-2002 to 2019-2020. This technique identifies the primary weather-related factors or predictors that influence crop yield, forming the basis for yield prediction using fuzzy logic. This endeavour serves as a solution to address future agricultural goals and to overcome some of the significant challenges faced by farmers. This includes methodology for yield estimation & prediction

2. MATERIALS AND METHODS

2.1 DATA

In pursuit of addressing the final objective of the study, essential data pertaining to various weather variables and parameters were procured. This valuable meteorological data was sourced from the distinguished Meteorology Department at CCS HAU, ensuring the inclusion of pertinent weather factors. The data includes monthly gathered values spanning over a 20-year period, from 2001-2002 to 2019-2020, encompassing nine key weather parameters. These parameters included maximum temperature, minimum temperature, saturation vapor pressure (SVP), relative humidity, wind speed, average wind speed, bright sun hours, pan evaporation, and rainfall. For the prediction of crop yields for Wheat, Mustard, Gram, and Barley, a multiple linear regression model was employed.

2.2 Fuzzy Sets

The concept of fuzzy sets, introduced by Lofti A. Zadeh in 1965, represents a profound generalization of classical sets. Unlike conventional crisp sets, where elements either wholly belong or do not belong to a set, fuzzy sets introduce a nuanced dimension. In the realm of fuzzy sets, elements can possess partial membership within the set, denoted by values in the interval [0, 1]. A fuzzy set $\widetilde{A}$ is represented by an ordered pair $\{[x, \mu_A(x)] \mid x \in X\}$, where x is the universe of discourse of set $\widetilde{A}$ & $\mu_A(x)$ is the membership function of $x \; in \; \widetilde{A}$ [3].

2.2.1 Fuzzy logic

Fuzzy Logic in the narrow sense is symbolic logic with a comparative notion of truth developed in the spirit of classical logic (syntax, semantics, axiomatization, truth – preserving deduction, completeness etc. both propositional and predicate logic) [4] and in a broad sense serves mainly as apparatus for fuzzy control, analysis of vagueness in natural language and several other application domains. It is one of the techniques of soft-computing i.e. computational methods tolerant to sub optimality and impreciseness (vagueness) and giving quick simple and sufficiently good solution.
If –then rules, fuzzy sets and fuzzy verbs are subjects of fuzzy Logic

1. A single fuzzy if- then rules asures the form if x is A than y is B
2. Where A and B are linguistic values defined by Fuzzy sets on the ranges (universe of discourse) X and Y, respectively
3. The if- part of the rule "x is A is called antecedent or premise, while than part "Y is B is called consequent or conclusion [5].

2.2.2 Fuzzy Decision Support System

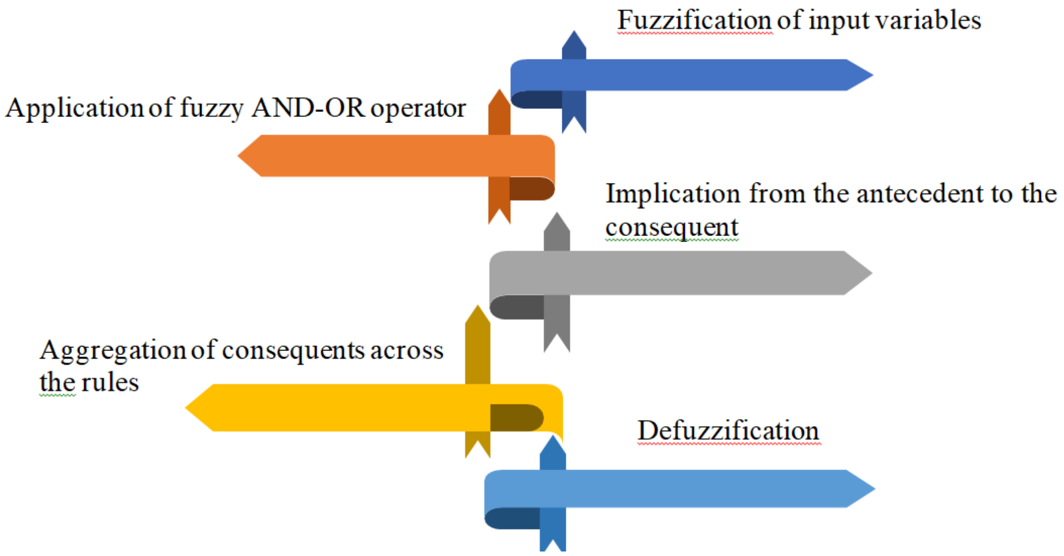
Building a fuzzy decision support system provides a method to present a complex problem in a simple and effective manner, the steps for the same include

1. Identifying the issues and selecting the kind of fuzzy system that best addresses them. The creation of a fuzzy-based decision support system consists of connecting many fuzzy modules.
2. Outlining the set of fuzzy heuristic rules after defining the input and output variables, their fuzzy values, and their membership function.
3. Selecting the fuzzification, defuzzification, and fuzzy inference methods
4. Experimenting with the prototype fuzzy system, establishing the target function between the input and output variables, modifying the fuzzy rules and membership functions as necessary, and fine-tuning the fuzzy system validation of outcomes [6].

Fuzzification: Using the membership function provided by the fuzzy knowledge base, a crisp input is transformed into a linguistic variable by this method.

Defuzzification: To make anything easier to understand, fuzzy values are converted to crisp values. Defuzzification is the process of taking a singleton or crisp output value from a fuzzy output. For defuzzification, we are utilizing Ebrahim Mamdani's approach in the present case [7].

Fuzzy Inference system



2.3 Development of the Fuzzy Model

The model development initiates with the application of multiple linear regression on a data set spanning over a period of 20 years, from 2001-2002 to 2019-2020 encompassing nine key weather parameters that included maximum temperature, minimum temperature, saturation vapor pressure (SVP), relative humidity, wind speed, average wind speed, bright sun hours, pan evaporation, and rainfall. This technique identifies the primary weather-related factors or predictors that influence crop yield, forming the basis for yield prediction using fuzzy logic [8]. The resulting trend equation, outlining the relationship between the mentioned weather variables and the yield of selected Wheat crop is

$Yield\ (trw) = -225.970 + 1.273\,trw - 149.578\,rf_6 + 31.718\,tmin_2 - 100.088\,svpe_6 - 28.832\,avs_2$, trw is trend values for Wheat yield, rf_6 corresponds to rainfall, $tmin_2$ indicates minimum temperature, $svpe_6$ stands for saturation vapor pressure, and avs_2 denotes average wind speed. The numerical coefficients in the suffixes of variables in this and further equations represent that particular day of a week.

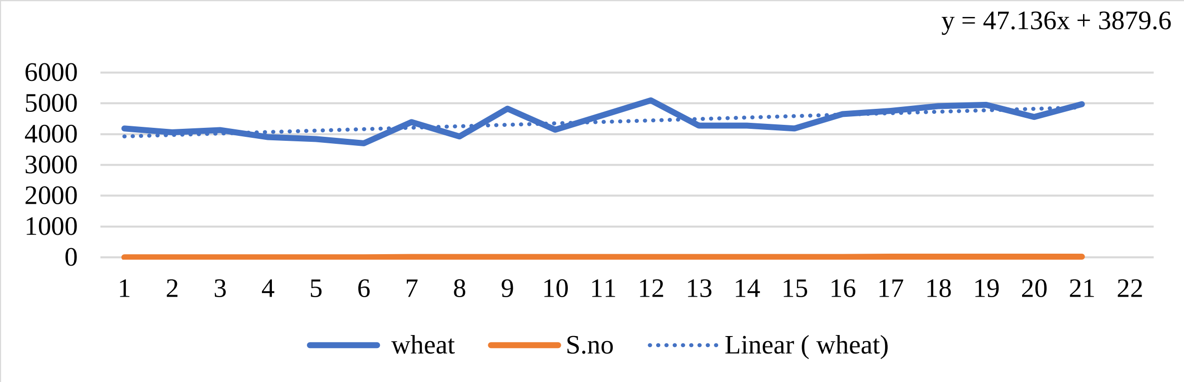


Figure 4.14 Trend equation of Wheat

Table 4.32 The actual and estimated yield of Wheat from year 2001-2002 to 2021-2022

S.no	**year**	**Wheat(kg/ hectare)**	
		Actual yield	**Predicted yield**
1	2001-2002	4182	4085.54
2	2002-2003	4062	4055.26
3	2003-2004	4135	4093.77
4	2004-2005	3901	3864.37
5	2005-2006	3844	3972.34
6	2006-2007	3704	3865.26
7	2007-2008	4392	4215.08
8	2008-2009	3920	3912.35
9	2009-2010	4829	4876.74
10	2010-2011	4139	4399.52
11	2011-2012	4622	4713.05
12	2012-2013	5098	4773.98
13	2013-2014	4273	4254.41
14	2014-2015	4273	4235.06
15	2015-2016	4180	4287.69
16	2016-2017	4648	4457.18
17	2017-2018	4758	4867.18
18	2018-2019	4914	4911.87
19	2019-2020	4955	5038.14
20	2020-2021	4560	4435.05
21	2021-2022		5011.26

The results from the regression model reveals that most prominent weather parameters that affect the crop yield are viz. minimum Temperature, Rainfall, Average Wind Speed & Relative Humidity. The gathered information is then stored in fuzzy knowledge rule base a component where knowledge is created, stored, organized, processed, and communicated. It is made up of a rule base and a database. The pieces required to define the language variable and rules utilizing If- THEN control constricts which are provided by the database [8]. The knowledge base's If (condition) sections of rules are matched against a collection of facts in the data base. The Mamdani rule formation is the basis of the rule knowledge used here. In order to define the rule-base we need to construct linguistic ranges for input weather variables and output yield. the weather variables were divided into three conceivable linguistic ranges minimum (min), optimum(opt), maximum(max) and yield of wheat was zoned into linguistic ranges poor, average, good.

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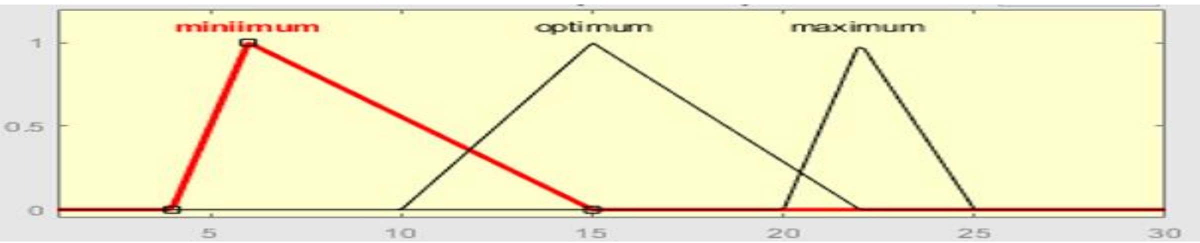
Table 4.33 Different linguistic ranges of weather parameters

Linguistic variable	Minimum (min)	Optimum (opt)	Maximum (max)
Temperature (^{0}C)	5-15	10-22	20-25
Rainfall (mm)	25-50	45-100	90-120
Avg. wind speed(km/hr)	1-3	1.5-5	4-9
Relative humidity (%)	50-60	55-100	90-120

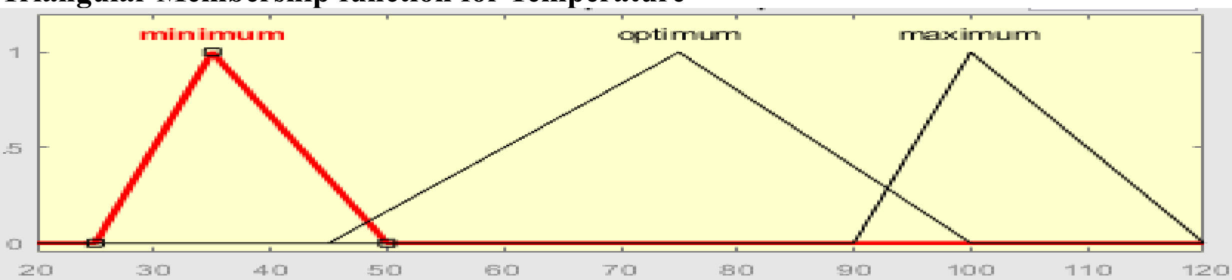
Table 4.34 Different linguistic ranges of Wheat yield in kg/hectare

Linguistic variable	Poor	Average	Good
Wheat	3200-3800	3500-4500	4000-5000

The input and output parameters were defined using triangular membership function. Expert's know and experimental conditions were taken into account while determining the number and range of membership functions. The rule editor of fuzzy model provided set of 81 fuzzy logic rules taking all possible interaction into consideration. These rules serves as a comprehensive guide for predicting Wheat crop yield based on varying weather conditions. These rules consider four essential weather variables: Temperature, Rainfall, Average wind speed, and Relative humidity, each categorized into linguistic variables. The rules demonstrate how different combinations of these variables impact crop yield, ranging from 'poor' under extreme adverse conditions to 'average' and 'good' when the weather conditions become more favourable.

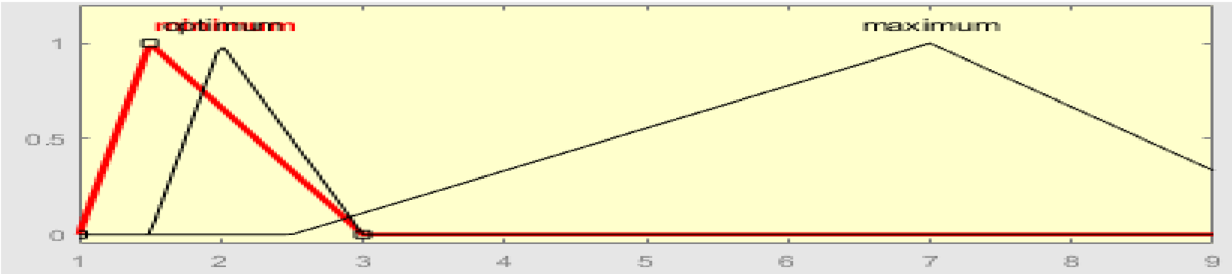


Triangular Membership function for Temperature



Triangular Membership function for Rainfall

Triangular Membership function for Relative Humidity



Triangular Membership function for Average Wind Speed

Table 4.35 Fuzzy logic-based rule table for prediction of yield

Rule	Temperature	Rainfall	Average wind Speed	Humidity	Predicted Yield
1	min	min	min	min	poor
2	min	min	min	max	poor
3	min	min	min	opt	poor
4	min	min	max	opt	poor
5	min	min	max	min	poor
6	min	min	max	max	poor
7	min	min	opt	min	poor
8	min	min	opt	max	poor
9	min	min	opt	opt	poor
10	min	max	min	min	poor
11	min	max	min	max	poor
12	min	max	min	opt	poor
13	min	max	max	opt	average
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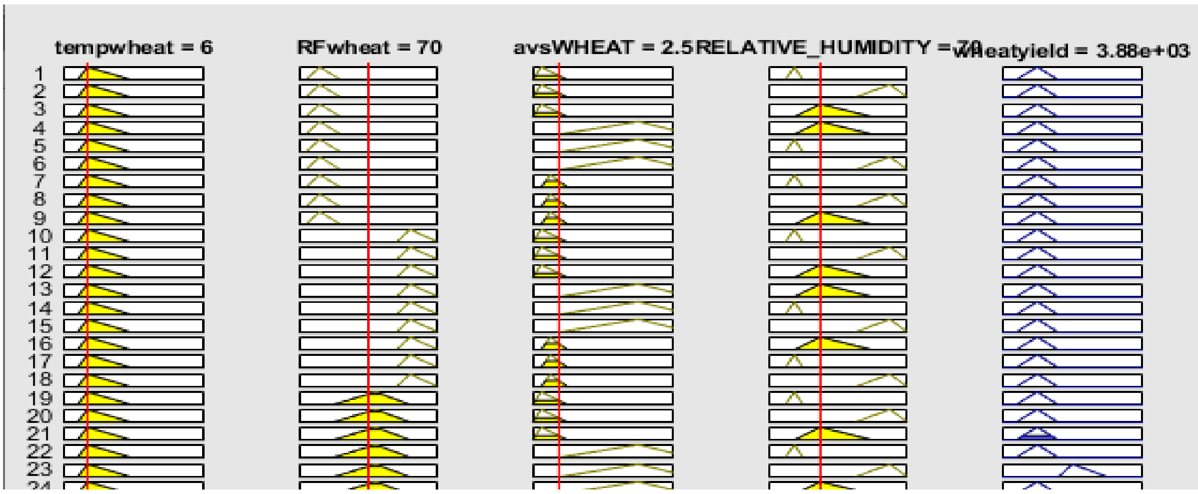
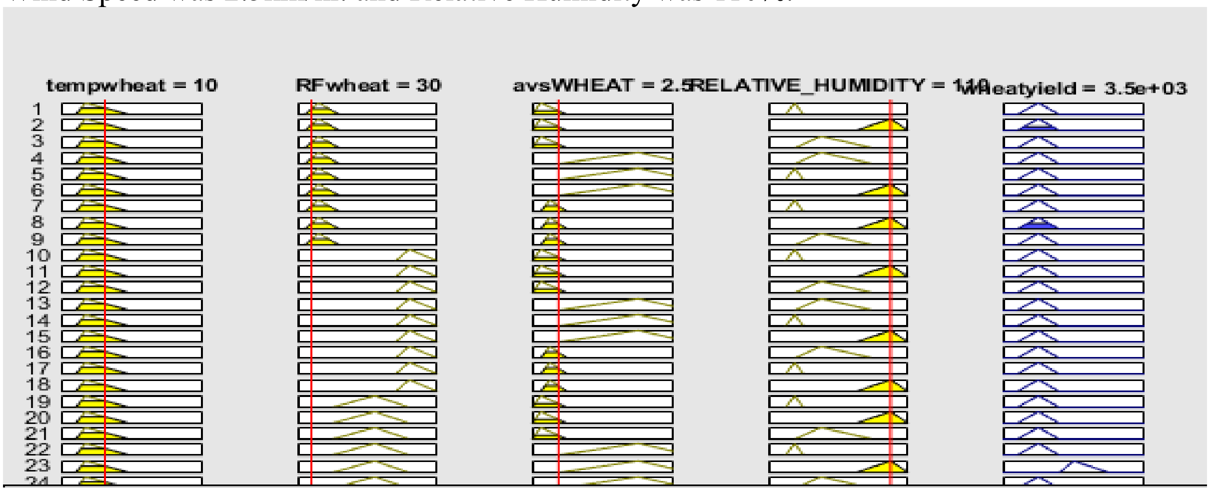
75	opt	opt	min	opt	good
76	opt	opt	max	min	average
77	opt	opt	max	max	average
78	opt	opt	max	opt	good
79	opt	opt	opt	min	good
80	opt	opt	opt	max	good
81	opt	opt	opt	opt	good

3. RESULTS AND DISCUSSION

In this study firstly the multiple linear regression model gives us the major predictor weather variables based on the correlation coefficient R (>0.8) [9] from initially categorized nine weather variables. The fuzzy rules then generated predicted the yield of wheat crop based on the fluctuations in climatic conditions. The fuzzy rule base predicted average yield i.e., approx.3880 kg/hectare when the Temperature was 6°C, Rainfall was 70mm, Average Wind Speed was 2.5km/hr. and Relative Humidity was 70%.



The yield was approx. 3500 kg/hectare when the Temperature was 10°C, Rainfall was 30mm, Average Wind Speed was 2.5km/hr. and Relative Humidity was 110%.



Absolutely, combining prior weather data with fuzzy logic is a powerful approach for crop yield prediction. Fuzzy logic, which is well-suited to handle imprecision, allows the model to account for the unpredictable nature of weather patterns, which can vary considerably from year to year. By analysing factors like temperature, rainfall, humidity, and average wind speed within this model, it helps farmers make informed decisions, especially under uncertain or fluctuating conditions. This predictive insight enables farmers to assess the likelihood of an optimal yield, helping them decide on the right crops and planting schedules, ultimately supporting better resource management and risk reduction in agriculture [10].

4. FUTURISTIC APPROACH

The real spot on is in pointing out the limitations of fuzzy models and the importance of acknowledging them to guide future research effectively. While fuzzy logic models offer advantages in handling the uncertainties of weather data and can produce valuable predictive insights, they are inherently sensitive to factors such as the quality of input data, choice of membership functions, and selection of variables [11]. These elements significantly impact the model's reliability and accuracy.

To enhance predictive capabilities, integrating additional variables like soil quality, nutrient levels, and resource availability is indeed a promising direction. Incorporating these factors could provide a more holistic view of crop yield influences. Moreover, complementing fuzzy models with statistical models or machine learning techniques could improve robustness and prediction accuracy, allowing for crossvalidation and comparison of results . Sensitivity analysis algorithms are also vital in this context; they can help quantify how changes in input variables affect yield predictions, thereby offering insights into which factors are most impactful.

5. CONCLUSION

Mathematical Models are effective and informative ways that help farmers to make well planned decisions for optimum returns. The use of fuzzy related models serves as one of the tools for above. Fuzzy logic takes advantage of already created simple rules resulting in equal or even less time consuming than the other conventional methods. The uncertainty related to a specific decision can easily incorporated in the model rule algorithm that makes a problem and its solution more realistic [12].
The results produced emphasis the efficacy of using fuzzy models in predicted the yield of wheat crop under the influence of alerting weather scenarios. Although the model generated efficient results but continuous refinement and validation is a must for its reliability and applicability for dealing with real world problems.

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